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Climatological Characterization, Trend Analysis, and SARIMA-Based Forecasting of Meteorological Variables at Toro Station, Bauchi State, Nigeria

Amobi Yekini[1]*, Mohammed S. Tsalha[1], Lungfa Collins Wuyep[1], Adamu Ubaidullahi Usman[1], Izzatu Tanko Idris[1], Madaki M. A[1], Abubakar Nuhu[1], Sani Yakubu Abdul'aziz[1], Nasiru Aliyu[1], Adamu Ibrahim[1].

[1]Centre for Geodesy and Geodynamics (CGG),
National Space Research and Development Agency (NASRDA), Toro, Bauchi State, Nigeria
***Corresponding author. E-mail:yekiniamo@yahoo.com.**

ABSTRACT
Reliable, high-frequency meteorological records remain critically scarce across north-central Nigeria, severely limiting the accuracy of agricultural advisories, water resource planning, and renewable energy assessments. This study presents the first systematic climatological analysis and predictive modelling exercise for Toro, Bauchi State, Nigeria, drawing on 136,606 validated 15-minute interval observations recorded by the Centre for Geodesy and Geodynamics (CGG) Davis Vantage Pro2 meteorological station between February 2022 and March 2026, representing 1,533 operational days with 92.80% data availability. Five parameters were analysed: air temperature, relative humidity, wind speed, rainfall, and solar radiation. Annual mean temperature exhibited a progressive warming signal, rising from 23.8 degrees C in 2022 to 24.6 degrees C in 2025 an increment of 0.8 degrees C over four years, consistent with accelerated warming documented across the West African Sahel-Sudan transition zone. Annual rainfall demonstrated extreme inter-annual variability (coefficient of variation: 63.5%), with totals of 1,668.7 mm, 1,793.0 mm, 875.2 mm, and 1,589.6 mm in 2022, 2023, 2024, and 2025, respectively the 2024 deficit representing a 51.2% collapse relative to 2023. Mean annual solar radiation reached 238.4 W/m2, confirming high photovoltaic potential. Using the 2022-2025 record as a training set, Seasonal Autoregressive Integrated Moving Average (SARIMA)(1,1,1)(1,1,1)[s] models were developed for each variable at weekly (20-step) and monthly (6-step) forecast horizons, with preliminary validation against January-March 2026 actual observations. Forecast outputs indicate peak temperatures of 30.9 degrees C in April 2026, near-zero rainfall through March, and a monsoon onset accumulation beginning in April. These findings provide a novel empirical baseline for Toro's climate, quantify the scale of meteorological risk facing the local agricultural economy, and demonstrate the operational value of station-level SARIMA forecasting for climate-sensitive planning in data-sparse tropical environments.
Keywords: climatological analysis; SARIMA forecasting; West African Monsoon; Sahel-Sudan transition; inter-annual rainfall variability; solar radiation; Toro; Bauchi State; Nigeria; automated weather station

1. INTRODUCTION

The global climate system is undergoing accelerating transformation, with its most consequential impacts concentrated in tropical and sub-tropical developing regions that possess the least adaptive capacity

(IPCC, 2021). Nowhere is this convergence of vulnerability and exposure more pronounced than across sub-Saharan West Africa, where the seasonal machinery of the West African Monsoon (WAM) the atmospheric engine governing the alternation between the rainy and dry seasons faces progressive disruption from rising sea surface temperatures, shifting atmospheric pressure gradients, and intensifying land-surface feedbacks (Niang et al., 2014). For nations like Nigeria, where agricultural production, water supply, and energy systems remain fundamentally tied to seasonal climatic cycles, this disruption translates directly into food insecurity, resource scarcity, and heightened disaster risk.

Nigeria, Africa's most populous nation with over 220 million inhabitants, encompasses five agro-ecological zones extending from the arid Sahelian north to the humid equatorial south (World Bank, 2023). The agricultural sector, which employs approximately 70% of the rural workforce and contributes roughly 24% of national GDP, is overwhelmingly rainfed, making the timing, intensity, and total volume of seasonal precipitation the most critical environmental determinant of national food production (FAO, 2022). North-central Nigeria encompassing Bauchi State and the Guinea-Sahel savanna transition zone sits among the most climate-sensitive regions of the country, characterised by high inter-annual rainfall variability, intense Harmattan dry seasons, and documented warming trends that exceed the global mean rate (Akinsanola & Ogunjobi, 2014; Bichet & Diedhiou, 2018).

Toro Local Government Area, located in Bauchi State at approximately 10.06 degrees N, 9.08 degrees E and an elevation of 600-700 m above sea level, represents precisely this class of understudied, climate-vulnerable environment. The area's elevated topographic setting generates orographic rainfall enhancement and micro-climatic conditions that diverge meaningfully from the broader regional averages inferred from more distant synoptic stations. Historically, however, this micro-climatic distinctiveness has gone unrecorded. The nearest conventional meteorological stations maintained by the Nigerian Meteorological Agency (NiMet) have been sited in more urban centers, leaving a significant observational gap that neither national forecasting models nor satellite-derived products have adequately resolved (Ogunjo et al., 2020).

The establishment of the Centre for Geodesy and Geodynamics (CGG) meteorological station in Toro in February 2022 marked a pivotal development in the region's scientific monitoring capacity. Equipped with a Davis Vantage Pro2 automatic weather station recording five atmospheric variables at 15-minute intervals, the facility represents one of the highest-resolution continuous monitoring systems operational in north-central Nigeria (Huntingford et al., 2019). By March 2026, the station had accumulated 136,606 valid observations across 1,533 operational days a dataset of exceptional temporal granularity and scientific value that, until this study, had not been subjected to systematic analysis.

The importance of such high-frequency ground-truth records for tropical climate science is well established. Conventional meteorological networks across West Africa are characterised by low spatial density, coarse temporal resolution, and chronic data gaps arising from infrastructure failures (Ogunjo et al., 2020). These limitations constrain the accuracy of numerical weather prediction, regional climate model parameterisation, and early warning system design. High-frequency station data provide the empirical foundation necessary to validate remote sensing products, improve model calibration, and support the development of locally relevant climate services services that are urgently needed given the intensifying climate pressures on the region's agricultural and water systems.

The application of Seasonal Autoregressive Integrated Moving Average (SARIMA) models to meteorological time series has been widely validated in the climatological literature. Box et al. (2015) established the foundational ARIMA-SARIMA framework; Adefisan and Abatan (2019) demonstrated its skill for Nigerian temperature series; and Ogunjo et al. (2020) confirmed its performance for seasonal rainfall forecasting at Nigerian stations. These results motivate the application of SARIMA modelling to the CGG Toro dataset, with the goal of generating operationally useful short-term forecasts for 2026 at both weekly and monthly temporal scales.

Against this background, this study pursues five specific objectives: (1) to characterise the temporal and seasonal variability of all five meteorological parameters at Toro using descriptive statistics and graphical analysis; (2) to identify and quantify inter-annual trends, particularly the warming trajectory of temperature and the high variability of annual rainfall; (3) to implement a rigorous data preprocessing and

quality assurance workflow capable of producing continuous time series from the raw 15-minute dataset; (4) to develop and validate SARIMA predictive models for each parameter at weekly and monthly scales; and (5) to generate calibrated meteorological forecasts for 2026 and assess their practical implications for agriculture, water resources, and energy planning in the Toro area. By achieving these objectives, this study delivers the first published, systematic climatological baseline for Toro, contributes novel empirical evidence to the literature on West African climate variability, and demonstrates the practical value of station-level statistical forecasting for climate-sensitive decision-making in a data-sparse tropical environment.

2. Study Area

The study area is centred on the Centre for Geodesy and Geodynamics (CGG) meteorological station located in Toro Local Government Area (LGA), Bauchi State, north-central Nigeria, at coordinates 10.06 degrees N, 9.08 degrees E and an elevation of approximately 600-700 metres above mean sea level (Figure 1). Bauchi State covers approximately 49,259 km2 of the north-central geopolitical zone and shares boundaries with Gombe, Yobe, Jigawa, Kano, Kaduna, Plateau, and Taraba States. The state's population, estimated at over 4.3 million in the 2006 national census and significantly higher in current projections, is predominantly rural, with a large proportion dependent on smallholder agriculture, pastoralism, and natural resource extraction.

Topographically, the Toro area is characterized by a dissected plateau landscape with rocky inselbergs, shallow valleys, and seasonally intermittent stream systems. The elevated terrain significantly higher than the surrounding lowland plains generates an orographic effect on precipitation, enhancing rainfall totals relative to valley-floor localities and producing a local temperature regime that is measurably cooler than the regional average during the wet season. This topographic distinctiveness makes the Toro micro-climate qualitatively different from conditions recorded at lower-elevation stations in Bauchi city (approximately 170 km to the east-northeast), reinforcing the need for locally sited meteorological observations.

The climate of Toro conforms to the tropical wet and dry classification (Koppen Aw), characterized by a pronounced seasonal alternation between a single wet season spanning approximately May to October and a prolonged dry season from November to April. The seasonal cycle is driven by the meridional migration of the Inter-Tropical Convergence Zone (ITCZ), which carries the moist southwesterly maritime air masses of the West African Monsoon northward during boreal summer and retreats southward as the dry, dust-laden Harmattan northeasterly winds advance from the Sahara during the dry season (Diro et al., 2011; Nicholson, 2013). Toro's position at approximately 10 degrees N places it within the transitional zone between the Guinea Savanna and Sudan Savanna ecoregions a position that makes rainfall totals and monsoon onset dates particularly sensitive to inter-annual variations in the strength and northern extent of the WAM.

The natural vegetation of the Toro area reflects this climatic regime: guinea savanna woodland with deciduous trees, shrub understorey, and grassy ground cover dominates the landscape, transitioning toward denser gallery forest along stream channels and degraded open land in areas subject to cultivation and wood fuel extraction. Land use is predominantly smallholder subsistence agriculture, with sorghum, millet, maize, groundnut, and cowpea as the principal food crops. Water supply relies heavily on shallow boreholes, hand-dug wells, and seasonal surface water sources that are directly dependent on the rainfall regime characterised in this study. The absence of reliable grid electricity across much of the Toro LGA makes the area a priority candidate for renewable energy deployment, for which the solar and wind data documented in this research provide an important empirical foundation.

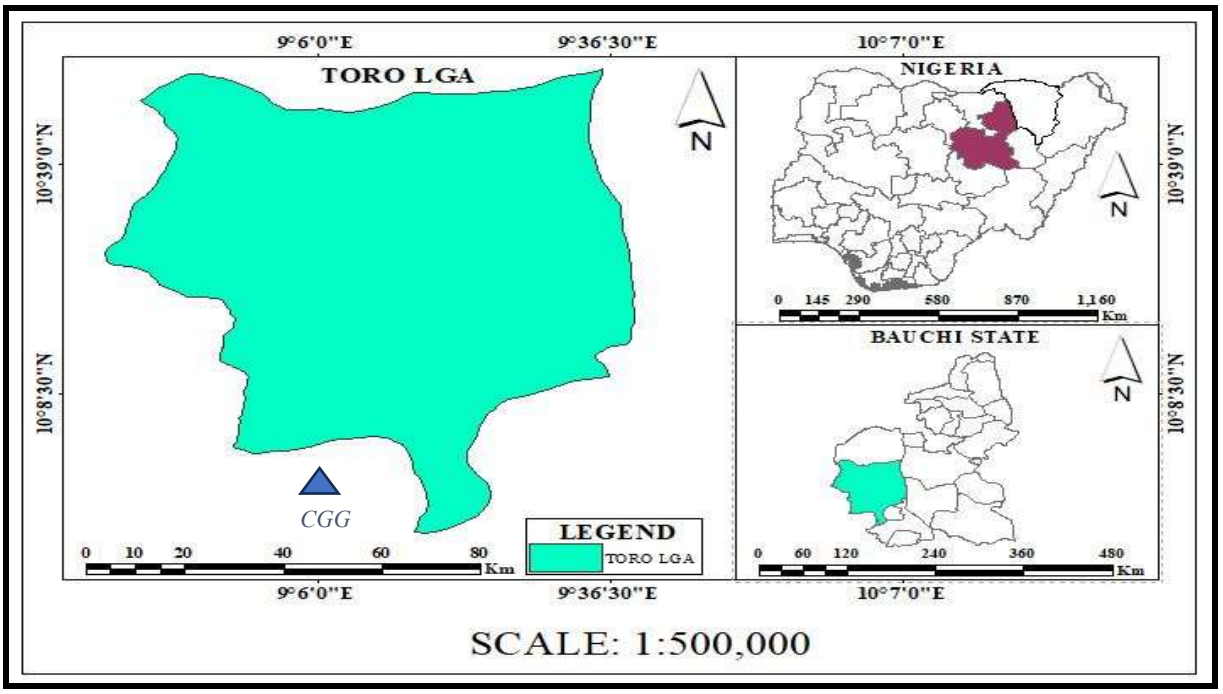

Figure 1. Study area map showing the location of the CGG Meteorological Station (Davis Vantage Pro2) in Toro, Bauchi State, north-central Nigeria (10.06 N, 9.08 E; elevation: 600-700 m a.m.s.l.). Inset shows Nigeria's position within Africa. Coordinate system: WGS 1984.

3. MATERIALS AND METHODS

3.1 Data Source and Instrumentation

The primary data source is the CGG Davis Vantage Pro2 automatic weather station (AWS) installed at Toro, Bauchi State, in February 2022. The instrument records five parameters at 15-minute intervals: air temperature (degrees C), relative humidity (%), wind speed (m/s), rainfall (mm), and solar radiation (W/m2). The station operates on solar-assisted power with battery backup. Data are logged to an onboard data logger and retrieved periodically for archiving. Over the study period, the station generated a total potential record of 147,024 observation intervals; 136,606 intervals were validated as complete readings, yielding a data availability rate of 92.80%. The primary source of missing records (7.20%) was power supply interruption, consistent with the dominant failure mode reported for automated weather networks in sub-Saharan Africa (Ogunjo et al., 2020). The complete observational record for this study encompasses February 2022 through March 2026, with the historical analysis concentrating on the complete calendar years 2022-2025.

3.2 Data Quality Assurance and Preprocessing

Raw 15-minute data were subjected to a two-stage quality assurance and preprocessing protocol. In the first stage, range checks were applied to flag physically implausible values based on established climatological bounds for the study region: temperature (-5 to 50 degrees C), relative humidity (0-100%), wind speed (0-50 m/s), rainfall (0-150 mm per 15-minute interval), and solar radiation (0-1600 W/m2). Observations outside these bounds were removed and treated as missing values.

In the second stage, missing records were imputed using a hierarchical approach validated for meteorological time series in tropical environments (Junninen et al., 2004). For internal gaps where missing values were bracketed by valid observations on both sides linear interpolation was applied, assuming a smooth linear trajectory between the nearest adjacent known values. For edge gaps occurring at the beginning or end of monthly data segments, forward filling (propagating the last known value forward) and backward filling (propagating the first known value backward) were applied. While these imputation methods preserve temporal continuity, they introduce a smoothing effect that may slightly

underrepresent short-duration extreme values, a limitation acknowledged throughout the analysis (Akinbobola & Ojo, 2018).

V missing = V start + (V end – V start) x [(T missing – T start) / (T end – T start)]

3.3 Temporal Aggregation

The cleaned and interpolated 15-minute series were aggregated to two temporal scales. For temperature, relative humidity, wind speed, and solar radiation, weekly means were computed as the arithmetic average of all valid or imputed readings within each seven-day window (ISO 8601 weeks); weekly totals were used for rainfall. Monthly aggregation followed the same principles, producing monthly mean values for continuous variables and monthly total rainfall. These aggregated series weekly and monthly served as the training inputs for the predictive modelling phase. Annual summary statistics (mean, maximum, minimum, and standard deviation) were computed for each calendar year from the monthly aggregated data.

3.4 SARIMA Predictive Modelling

Meteorological forecasting was performed using Seasonal Autoregressive Integrated Moving Average (SARIMA) models, which extend the classical Box-Jenkins ARIMA framework to explicitly represent seasonal autocorrelation structures (Box et al., 2015). The general SARIMA$(p,d,q)(P,D,Q)[s]$ model notation specifies: p (non-seasonal autoregressive order), d (non-seasonal differencing), q (non-seasonal moving average order), P (seasonal autoregressive order), D (seasonal differencing), Q (seasonal moving average order), and s (seasonal period). A standardised parameterisation of SARIMA(1,1,1)(1,1,1)[s] was adopted for all five variables at both temporal scales, following the approach validated for tropical meteorological series by Adefisan and Abatan (2019). The seasonal period was set to s=52 for weekly models and s=12 for monthly models. The complete 2022-2025 aggregated series constituted the training dataset. Models were fitted using the Python statsmodels library SARIMAX module. Forecast horizons were set to 20 steps (weeks) and 6 steps (months), both commencing from early January 2026, with 95% prediction intervals computed for each forecast step.

Table 1. SARIMA Model Configuration Summary for All Five Meteorological Variables.

Configuration Aspect	Weekly Forecast Model	Monthly Forecast Model
Training data	Weekly series, 2022-2025	Monthly series, 2022-2025
SARIMA order (p,d,q)(P,D,Q)[s]	(1,1,1)(1,1,1)[52]	(1,1,1)(1,1,1)[12]
Forecast horizon	20 steps (20 weeks)	6 steps (6 months)
Forecast start date	05 January 2026	31 January 2026
Variables modelled	Temperature, RH, Wind, Rain, Solar	Temperature, RH, Wind, Rain, Solar
Validation period	Jan-Mar 2026 actuals	Jan-Mar 2026 actuals
Software environment	Python 3.x - statsmodels SARIMAX	Python 3.x - statsmodels SARIMAX

Note: RH = relative humidity. SARIMA = Seasonal Autoregressive Integrated Moving Average. Seasonal periods: s=52 (weekly); s=12 (monthly).

3.5 Model Validation and Post-Processing

Preliminary model validation was conducted by visually comparing forecast outputs against partial 2026 actual observations recorded at the CGG station during January-March 2026. For rainfall, SARIMA models occasionally generated small negative forecast values during expected dry season periods, a well-documented artefact of linear Gaussian models applied to a non-negative bounded variable. Consistent with standard meteorological practice (Adefisan & Abatan, 2019), all negative rainfall forecasts were re-interpreted as effectively zero precipitation. All data processing and modelling operations were

implemented in Python, using pandas and NumPy for data manipulation, stats models for SARIMA fitting, and matplotlib for visualization.

3.6 SARIMA Model Mathematical Formulation

The Seasonal Autoregressive Integrated Moving Average (SARIMA) model extends the classical Box-Jenkins ARIMA framework to accommodate seasonal patterns in time series data. The general SARIMA model is expressed as:

$$\Phi_p(B^s)\phi_p(B)(1-B)^d(1-B^s)^D Y_t = \Theta_Q(B^s)\theta_q(B)\varepsilon_t \quad \ldots (1)$$

where:

- Y_t is the observed time series at time t
- B is the backward shift operator, defined as $B^k Y_t = Y_{t-k}$
- B^s is the seasonal backward shift operator, where s denotes the seasonal period
- $\phi_p(B) = 1 - \phi_1 B - \phi_2 B^2 - \cdots - \phi_p B^p$ is the non-seasonal autoregressive (AR) polynomial of order p
- is the non-seasonal moving average (MA) polynomial of order q
- $\Phi_p(B^s) = 1 - \Phi_1 B^s - \Phi_2 B^{2s} - \cdots - \Phi_p B^{Ps}$ is the seasonal AR polynomial of order P
- $\Theta_Q(B^s) = 1 + \Theta_1 B^s + \Theta_2 B^{2s} + \cdots + \Theta_Q B^{Qs}$ is the seasonal MA polynomial of order Q
- $(1-B)^d$ is the non-seasonal differencing operator of order d
- $(1-B^s)^D$ is the seasonal differencing operator of order D
- ε_t is a white noise process with mean zero and constant variance σ^2

For the specific SARIMA$(1,1,1)(1,1,1)[s]$ model applied in this study, the equation simplifies to:

$$(1-\Phi_1 B^s)(1-\phi_1 B)(1-B)(1-B^s)Y_t = (1+\Theta_1 B^s)(1+\theta_1 B)\varepsilon_t$$

Expanding the differencing operators:

The expanded form provides the complete autoregressive representation:

$$Y_t = (1+\phi_1)Y_{t-1} + (1+\Phi_1)Y_{t-s} - (1+\phi_1+\Phi_1+\phi_1\Phi_1)Y_{t-s-1} + \phi_1 Y_{t-2} + \Phi_1 Y_{t-2s} - \phi_1\Phi_1 Y_{t-s-2} + \varepsilon_t + \theta_1\varepsilon_{t-1} + \Theta_1\varepsilon_{t-s} + \Theta_1\theta_1\varepsilon_{t-s-1}$$

… (2)

For weekly models, the seasonal period was set to $s = 52$, representing the 52-week annual cycle. For monthly models, $s = 12$, representing the 12-month annual cycle. Model parameters were estimated using maximum likelihood estimation (MLE), which maximises the log-likelihood function:

$$\mathcal{L}(\theta) = -\frac{n}{2}\ln(2\pi) - \frac{n}{2}\ln(\sigma^2) - \frac{1}{2\sigma^2}\sum_{t=1}^{n}\varepsilon_t^2 \quad \text{… (3)}$$

where $\theta = (\phi_1, \theta_1, \Phi_1, \Theta_1, \sigma^2)$ represents the vector of model parameters, and n is the number of observations in the training series.

Forecasts were generated using the recursive forecasting equation:

$$\hat{Y}_{t+h|t} = E[Y_{t+h} \mid \mathcal{F}_t] \quad \text{… (4)}$$

where $\hat{Y}_{t+h|t}$ is the h-step ahead forecast conditional on the information set $\mathcal{F}_t$ available at time t. The associated 95% prediction intervals were computed as:

$$\hat{Y}_{t+h|t} \pm 1.96 \times \sqrt{\mathrm{Var}(\varepsilon_{t+h} \mid \mathcal{F}_t)} \quad \text{… (5)}$$

where the forecast variance accounts for both the model's stochastic error and parameter estimation uncertainty.

4. RESULTS

4.1 Data Completeness and Quality Assessment

Over the entire study period from February 2022 to March 2026 (1,533 operational days), the CGG station recorded 136,606 valid 15-minute observations out of a potential 147,024, yielding an overall data availability rate of 92.80%. Missing data were predominantly attributable to power supply interruptions, consistent with findings from comparable automated weather networks across sub-Saharan Africa (Ogunjo et al., 2020). Following the application of the two-stage preprocessing protocol, a complete, interpolated time series was obtained for each parameter, forming the analytical foundation for all subsequent analyses.

4.2 Air Temperature

4.2.1 Annual Statistics and Seasonal Variability

Annual mean temperature at the CGG Toro station rose progressively across the four-year study period, from 23.8 degrees C in 2022 to 24.6 degrees C in 2025 a total increment of 0.8 degrees C in four years (Table 2). This warming trajectory, while based on a short record, is directionally consistent with the accelerated warming reported across the West African Sahel-Sudan transition zone (Bichet & Diedhiou,

2018). Standard deviations increased from 4.4 degrees C in 2022 to 4.9 degrees C in 2025, indicating a widening of the annual temperature range. The highest recorded temperature was 39.2 degrees C in March 2024, during the peak of the pre-monsoon dry season. The lowest minimum was 11.1 degrees C in December 2022, reflecting the strong radiative cooling associated with the cloud-free, dry Harmattan season.

The seasonal temperature cycle follows a characteristic bimodal annual envelope. Temperatures are lowest in December-January (the cool-dry Harmattan season), rise sharply through February-April as solar angles increase and cloud cover remains absent, peak in March-April before declining as monsoon cloud cover and evaporative cooling moderate conditions from May onwards, and reach a secondary minimum during the peak wet season in July-August. The analysis of 15-minute interval data identified 6,724 heatwave events (periods of consecutive 15-minute records exceeding a locally defined heat stress threshold) and 6,812 cold spell events a finding with direct implications for agricultural heat stress assessment and human health planning that would be completely invisible in conventional daily or monthly average records.

Table 2. Annual Air Temperature Statistics at CGG Toro Station (2022-2025).

Year	Mean Temp (C)	Max Temp (C)	Min Temp (C)	Std Dev (C)	Range (C)
2022	23.8	38.9	11.1	4.4	27.8
2023	24.2	37.3	12.0	4.6	25.3
2024	24.3	39.2*	11.9	4.9	27.3
2025	24.6	38.4	12.3	4.9	26.1
4-yr Mean	24.2	—	—	4.7	—

*Note: * = Study period absolute maximum (39.2 C, March 2024). Std Dev = standard deviation of monthly mean temperatures within each year. Range = annual max minus annual min.*

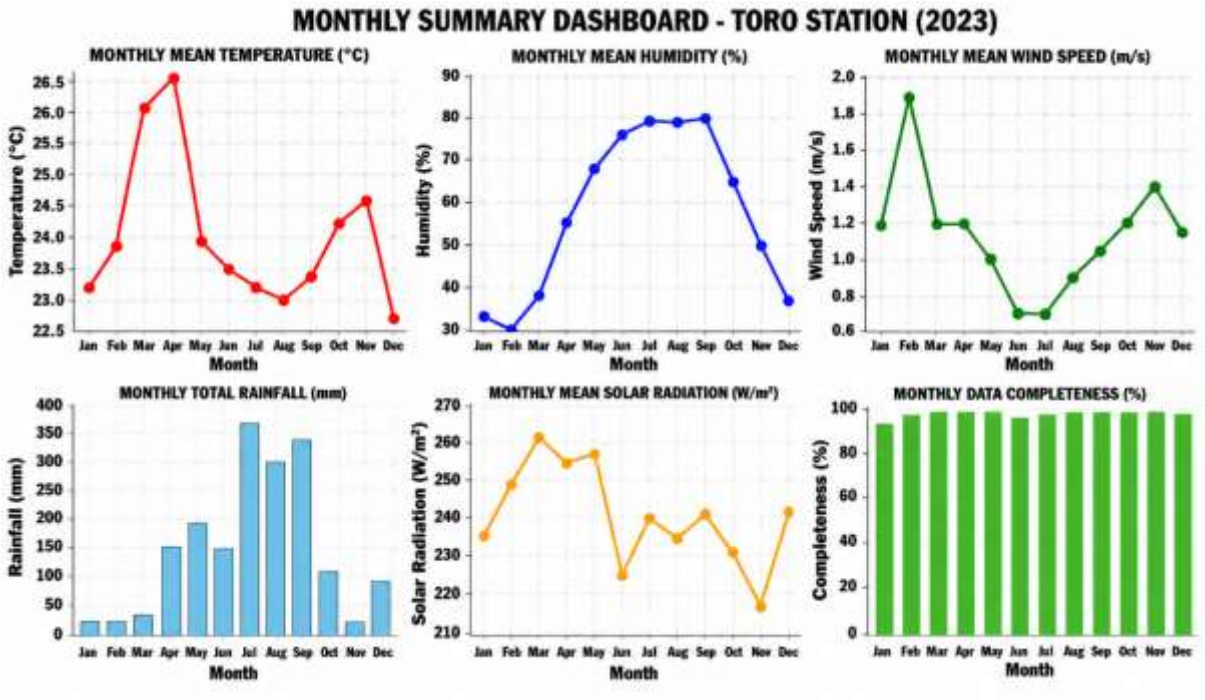

Figure 2. Monthly mean air temperature variation at CGG Toro Station (2022-2025), illustrating the pre-monsoon temperature peak (March-April) and wet-season depression (July-August).

4.3 Rainfall

4.3.1 Annual Totals and Inter-Annual Variability

Annual rainfall at CGG Toro demonstrated extreme inter-annual variability across the study period. Total annual precipitation was 1,668.7 mm in 2022, 1,793.0 mm in 2023, 875.2 mm in 2024, and 1,589.6 mm in 2025 (Table 3). The coefficient of variation (CV) calculated from these four annual totals is 63.5% a value substantially exceeding the 20-40% range typically reported for established long-record synoptic stations in northern Nigeria and reflecting the high sensitivity of rainfall at this transitional location to inter-annual variations in WAM strength and ITCZ migration (Nicholson, 2013). The 2024 annual total of 875.2 mm is the most significant anomaly of the observational period, representing a 51.2% reduction relative to the 2023 total and falling well below the four-year mean of 1,481.6 mm. This deficit is broadly consistent with the neutral-to-warm ENSO conditions that prevailed during the 2024 West African monsoon season and the known suppressive effect of warm equatorial Pacific sea surface temperatures on monsoon rainfall across the Guinea-Sahel zone (Nicholson, 2013).

Table 3. Annual Rainfall Statistics at CGG Toro Station (2022-2025).

Year	Total Rain (mm)	Wet Season	Peak Month(s)	Anomaly vs Mean	CV (%)
2022	1,668.7	May-Oct	Aug-Sep	+12.6%	—
2023	1,793.0	May-Oct	Jul-Aug	+21.0%	—
2024	875.2	Jun-Sep	Aug	-40.9%	—
2025	1,589.6	May-Oct	Jul-Aug	+7.3%	—
4-yr Mean	1,481.6	—	—	—	63.5

Note: Anomaly calculated relative to 4-year mean (1,481.6 mm). CV = coefficient of variation across 4-year record. Wet season defined as months with >60 mm total rainfall.

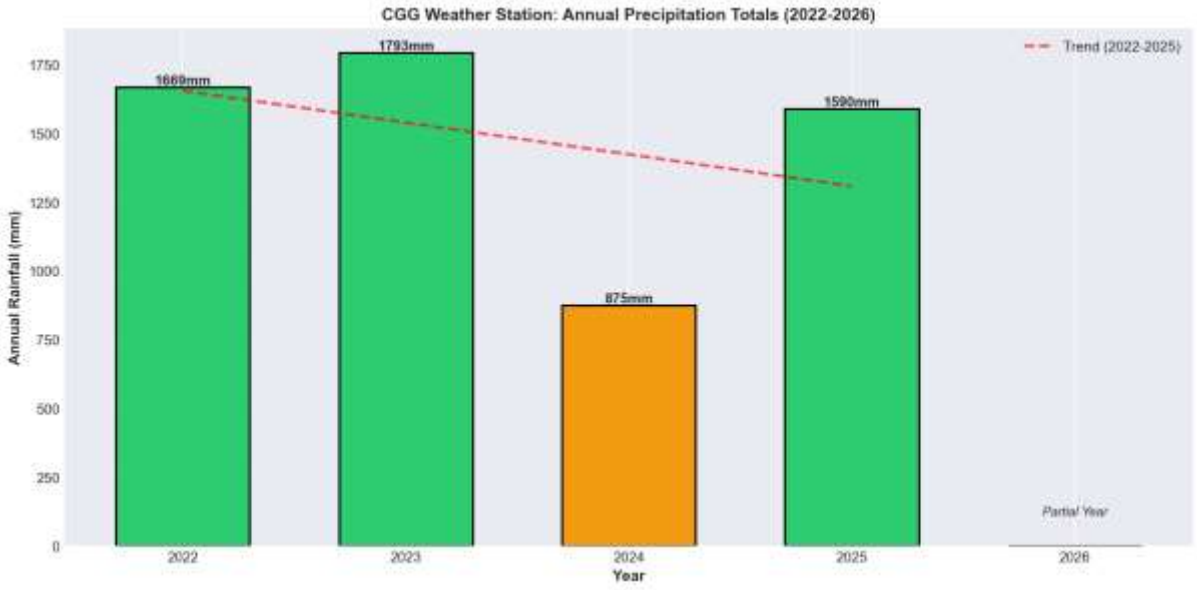

Figure 3: Yearly rainfall distribution from CGG station records

Note: Annual and monthly rainfall distribution at CGG Toro Station (2022-2025), illustrating the unimodal wet season (May-October) and the severe 2024 annual deficit (875.2 mm; -40.9% anomaly).

4.3.2 Seasonal Structure and Monsoon Onset

The seasonal structure of rainfall at Toro is unimodal, with all significant precipitation concentrated in the May-October wet season and near-zero totals during the November-April dry season. This pattern is consistent with the expected rainfall regime for the Guinea-Sudan savanna transition zone, where the ITCZ passes northward over the study area once per year, typically achieving its northernmost extent in August before retreating southward (Diro et al., 2011). Peak monthly rainfall totals typically occurred in July, August, or September across the four study years (see Figure 2). The onset of meaningful rainfall

operationally defined as the period when weekly accumulations cross a threshold sufficient to support crop germination generally occurred in late April to early May, a finding directly relevant to agricultural planning calendars.

4.4 Relative Humidity

Relative humidity at Toro exhibited a seasonal variation tightly coupled to the WAM cycle (Table 4). During the dry season (December-February), monthly mean relative humidity regularly fell below 30%, with an absolute minimum of 21.8% recorded in February 2022. These extremely low values reflect the deep incursion of dry continental Harmattan air and are associated with high evapotranspiration demand, fire risk, and respiratory health impacts. Conversely, during the core wet season (July-September), mean monthly relative humidity exceeded 85% across all years, frequently reaching diurnal maxima of 98-99% during and immediately following convective rainfall events. Annual mean relative humidity ranged from 56.0% (2025) to 62.4% (2023), with the lower 2025 mean reflecting the anomalously limited wet season duration that year (see Figure 4).

Table 4. Annual Relative Humidity Statistics at CGG Toro Station (2022-2025).

Year	Annual Mean (%)	Dry Season Min (%)	Wet Season Max (%)	Std Dev (%)
2022	59.6	21.8 (Feb)	98.4 (Aug)	22.8
2023	62.4	23.1 (Jan)	98.8 (Sep)	22.2
2024	58.3	22.5 (Feb)	97.9 (Aug)	23.5
2025	56.0	24.0 (Jan)	98.6 (Sep)	22.9
4-yr Mean	59.1	—	—	22.9

Note: Dry season minimum and wet season maximum are absolute monthly mean extremes within each year. Std Dev = standard deviation across all monthly means.

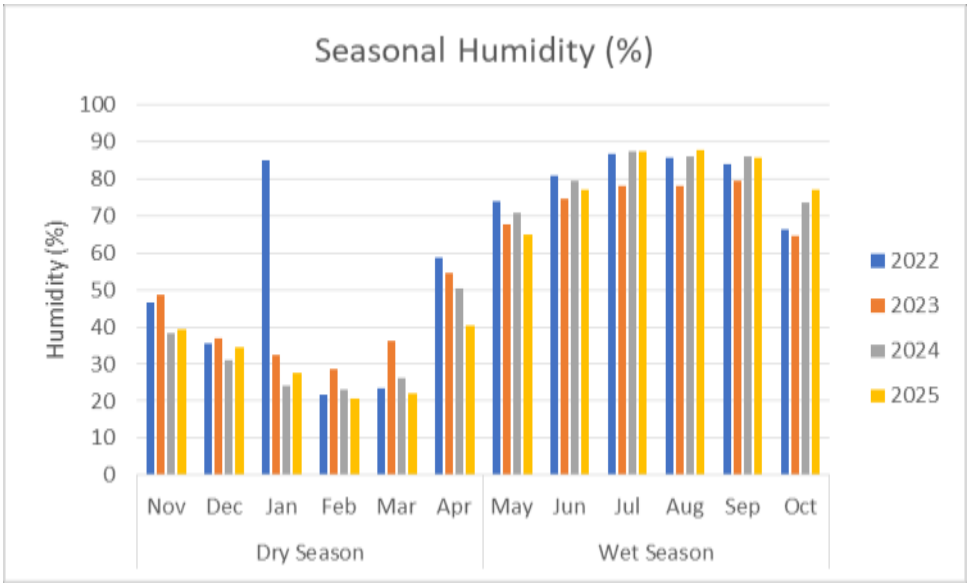

Figure 4: Seasonal relative humidity variation from CGG station records

Note: Seasonal variation of relative humidity at CGG Toro Station (2022-2025), showing the sharp dry-to-wet season transition and the inverse relationship with temperature.

4.5 Wind Speed and Solar Radiation

Annual mean wind speeds at the CGG Toro station remained consistently low across the study period, ranging from 1.2 m/s in 2023 to 1.5 m/s in 2024 and 2025 (Table 5). The low mean values reflect the generally calm ambient wind environment of the inland Guinea Savanna. However, peak gust speeds reaching 12.5 m/s were recorded in May 2025, associated with the leading squall lines of early monsoon convective cells events of particular relevance for wind hazard assessment and wind energy resource characterisation.

Solar radiation followed a well-defined and practically important seasonal cycle (Table 5). Mean annual solar radiation rose from 225.7 W/m2 in 2022 to 249.0 W/m2 in 2025, with a four-year mean of approximately 238.4 W/m2 (see Figure 5). Peak monthly means consistently occurred during the dry season months of March through May shown in Figure 2, when cloud cover is minimal and solar zenith angles are near-overhead. The absolute maximum instantaneous reading of 1,523 W/m2 is consistent with the theoretical clear-sky maximum for this latitude. The documented mean annual irradiance of 238.4 W/m2 places Toro firmly within the high-solar-resource category recognised as economically viable for photovoltaic power generation.

Table 5. Annual Wind Speed and Solar Radiation Statistics at CGG Toro Station (2022-2025).

Year	Wind Mean (m/s)	Wind Max (m/s)	Solar Mean (W/m2)	Solar Max (W/m2)	Solar Trend
2022	1.3	10.8	225.7	1,412	Baseline
2023	1.2	11.3	231.5	1,489	+2.6%
2024	1.5	11.9	237.8	1,523*	+5.4%
2025	1.5	12.5**	249.0	1,507	+10.3%
4-yr Mean	1.4	—	238.4	—	—

*Note: * = Study period absolute maximum solar radiation (1,523 W/m2, 2024). ** = Study period maximum wind gust (12.5 m/s, May 2025). Solar trend = % increase relative to 2022 mean.*

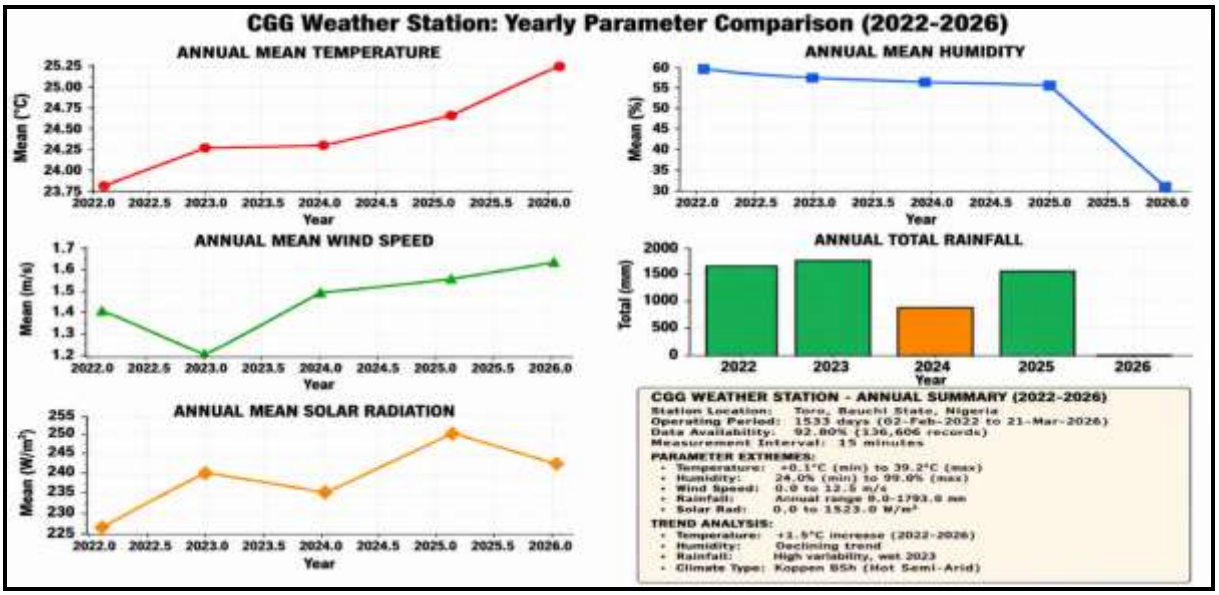

Figure 5: Annual distribution of meteorological parameters from CGG station records
Note: Annual distribution of solar radiation (W/m2) and wind speed (m/s) at CGG Toro Station (2022-2025), showing the seasonal cycle and the slight increasing trend in mean annual irradiance.

4.6 Integrated Annual Climatological Summary

Table 6 presents a consolidated inter-annual comparison of all five meteorological parameters across the study period, enabling a holistic assessment of year-to-year variability that defines the local climate risk landscape.

Table 6. Integrated Annual Meteorological Summary, CGG Toro Station (2022-2025).

Parameter	2022	2023	2024	2025
Mean temperature (C)	23.8	24.2	24.3	24.6
Maximum temperature (C)	38.9	37.3	39.2	38.4
Minimum temperature (C)	11.1	12.0	11.9	12.3
Total rainfall (mm)	1,668.7	1,793.0	875.2	1,589.6
Annual rainfall anomaly	+12.6%	+21.0%	-40.9%	+7.3%
Mean relative humidity (%)	59.6	62.4	58.3	56.0
Mean wind speed (m/s)	1.3	1.2	1.5	1.5

Maximum wind gust (m/s)	10.8	11.3	11.9	12.5
Mean solar radiation (W/m2)	225.7	231.5	237.8	249.0
Data availability (%)	90.8	93.5	92.1	94.8

Note: All values derived from preprocessed and quality-controlled CGG station dataset. Annual rainfall anomaly calculated relative to 4-year mean (1,481.6 mm).

4.7 SARIMA Forecast Results for 2026

4.7.1 Monthly Forecast (January-June 2026)

SARIMA(1,1,1)(1,1,1)[12] models fitted to the 2022-2025 monthly training series generated coherent 6-month forecasts for all five parameters (Table 7, Figure 6). Temperature is forecast to rise from 22.4 degrees C in January to a peak of 30.9 degrees C in April before declining with monsoon onset. Relative humidity is predicted to remain very low (below 40%) through the first quarter before rising sharply to 76.0% in June. Rainfall forecasts indicate effectively zero precipitation from January through March, followed by mounting accumulation: 57.7 mm in April, 164.2 mm in May, and 144.1 mm in June, signalling the onset of the rainy season. Solar radiation is forecast to peak at 273.2 W/m2 in May before declining slightly as monsoon cloud cover increases. The weekly SARIMA(1,1,1)(1,1,1)[52] models further resolved the week centred on 3 May 2026 as the first week of significant anticipated precipitation (49.7 mm), consistent with the typical monsoon onset window documented in the historical record.

Table 7. SARIMA Monthly Forecast Summary for CGG Toro Station (January-June 2026).

Month	Temp (C)	Humidity (%)	Wind (m/s)	Rain (mm)	Solar (W/m2)
January 2026	22.4	29.7	1.36	~0 (dry)	241.6
February 2026	25.3	19.8	1.53	~0 (dry)	242.5
March 2026	30.7	20.8	1.78	~0 (dry)	272.0
April 2026	30.9*	39.9	1.67	57.7	271.7
May 2026	27.1	63.9	1.56	164.2	273.2**
June 2026	25.2	76.0	1.38	144.1	264.3

*Note: * = Forecast temperature peak (30.9 C, April). ** = Forecast solar peak (273.2 W/m2, May).*
Negative raw SARIMA rainfall values for Jan-Mar re-interpreted as effectively zero, consistent with Adefisan and Abatan (2019).

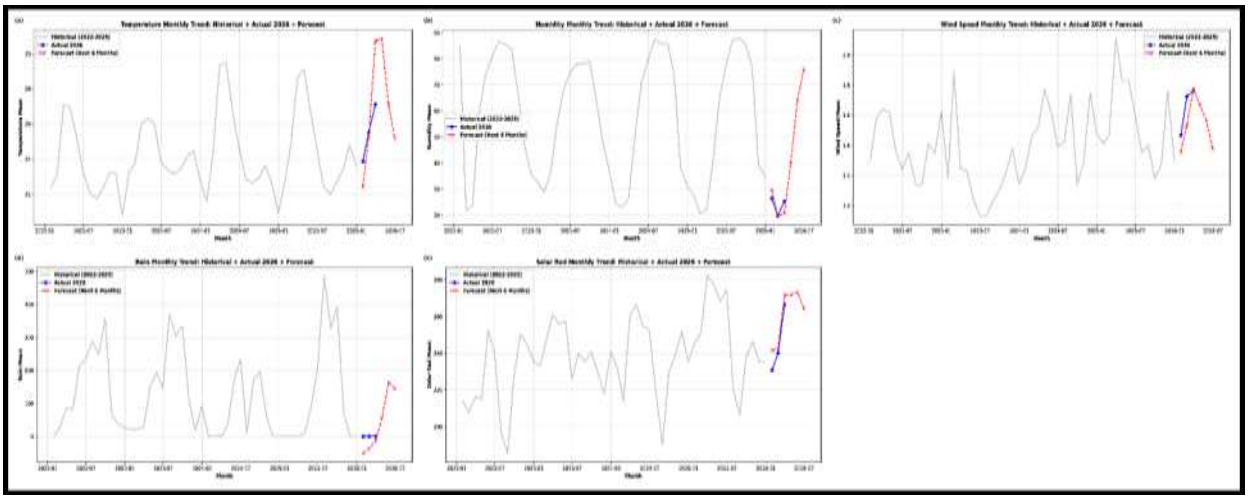

Figure 6. Monthly SARIMA forecast outputs for all five meteorological parameters (January-June 2026), integrating 2022-2025 historical training data, partial 2026 actual observations, and the model forecast trajectory with 95% prediction intervals.

4.7.2 Weekly Forecast (January-May 2026)

The weekly SARIMA(1,1,1)(1,1,1)[52] models provided a finer-grained picture of the seasonal transition across the 20-week forecast horizon. The forecast resolves the week centred on 3 May 2026 as the first week of significant anticipated precipitation (49.7 mm), consistent with the typical monsoon onset window documented in the historical record. Prior weeks show near-zero rainfall values, confirming the extended dry period expected through March and into April.

Table 8. Selected Weekly SARIMA Forecast Snapshot for CGG Toro Station (January-May 2026).

Week starting	Temp (C)	Humidity (%)	Wind (m/s)	Rain (mm)	Solar (W/m2)
05 Jan 2026	21.6	32.4	1.31	~0	238.4
02 Feb 2026	24.8	22.1	1.48	~0	245.2
02 Mar 2026	29.4	21.5	1.72	~0	268.6
30 Mar 2026	31.2	35.8	1.65	14.3	274.1
27 Apr 2026	28.5	55.6	1.58	38.9	272.8
03 May 2026	26.9	68.4	1.52	49.7	269.4

Note: Selected representative weeks shown. Full 20-week forecast available from corresponding author. All negative raw rainfall values re-interpreted as effectively zero (dry conditions).

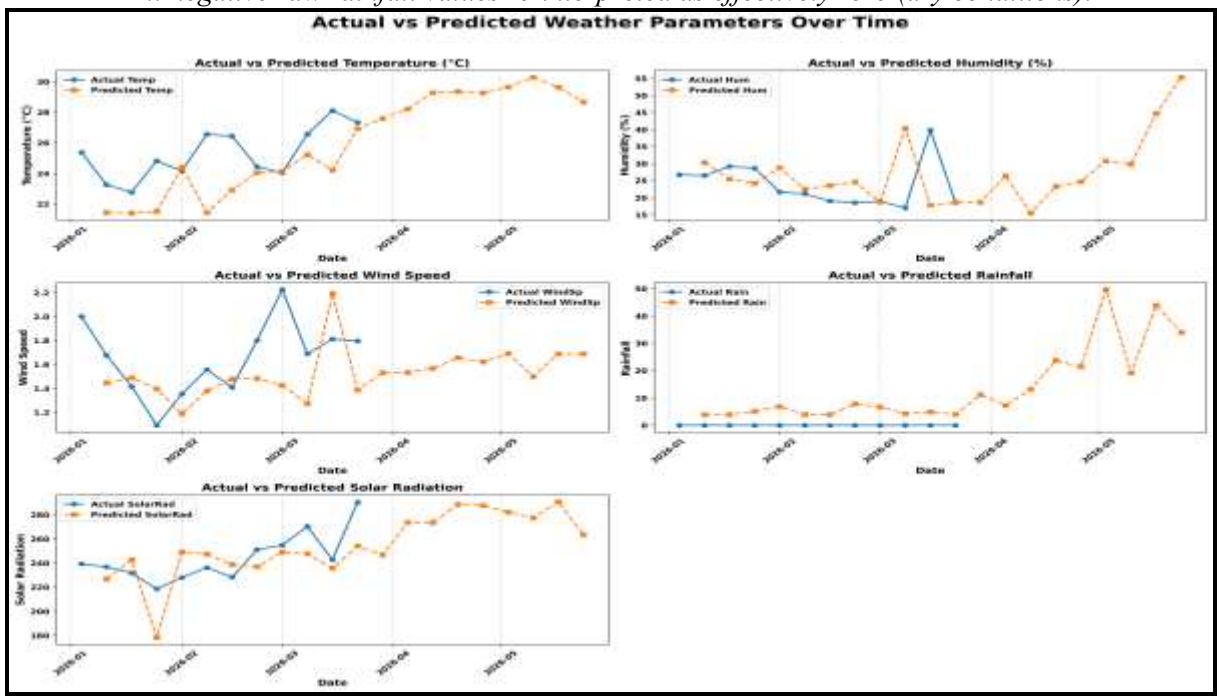

Figure 7. Weekly SARIMA forecast for the 20-week horizon (January-May 2026), integrating 2022-2025 historical training data, partial 2026 actual observations, and forecast trajectories with 95% prediction intervals for all five parameters.

5. DISCUSSION

5.1 The Warming Temperature Signal: Local Evidence of a Regional Trend

The progressive increase in annual mean temperature from 23.8 degrees C to 24.6 degrees C between 2022 and 2025 an increment of 0.8 degrees C in four years constitutes a striking, if temporally limited, warming signal at the CGG Toro station. Placed in the context of the broader literature, this finding is directionally consistent with though potentially accelerated relative to the centennial warming trends documented by Akinsanola and Ogunjobi (2014), who reported increases of 0.3-0.5 degrees C per decade at NiMet stations across northern Nigeria. Bichet and Diedhiou (2018) similarly noted that the Sahel-Sudan transition zone has experienced warming rates exceeding the global mean, driven by a combination

of greenhouse gas forcing and regional land-surface changes including deforestation and rangeland degradation.

The significance of the absolute temperature extremes recorded in this dataset particularly the 39.2 degrees C maximum in March 2024 extends well beyond academic interest. Pre-monsoon heat events at such intensities impose severe heat stress on smallholder farmers engaged in land preparation, sowing, and early crop establishment activities precisely the period when agricultural labour demands are highest and human bodies are least acclimatised following the cooler Harmattan season. The IPCC (2021) has identified increasing frequency and intensity of heat extremes as a near-term certainty under all emission scenarios, and the granularity of the CGG 15-minute dataset which enabled the identification of 6,724 separate heatwave events provides the kind of detailed empirical foundation necessary for locally calibrated heat health risk assessments that currently do not exist for the Toro area.

5.2 Extreme Rainfall Variability: The Most Critical Identified Climate Risk

The 2024 rainfall anomaly just 875.2 mm against a four-year mean of 1,481.6 mm is unquestionably the most consequential finding of this study from an agricultural and food security perspective. A year-on-year reduction of 51.2% in annual rainfall, coming immediately after the exceptionally wet 2023 season, represents exactly the kind of devastating inter-annual swing that the literature on West African climate has long characterised as an endemic and defining feature of the Sahelian and sub-Sahelian environment (Nicholson, 2013). For smallholder farmers in Toro who made planting decisions in 2024 on the basis of the favourable 2023 experience investing in fertiliser and expecting a robust season the dramatic shortfall would have translated into widespread crop failure, feed shortages for livestock, and a sharp decline in household food security.

The coefficient of variation of 63.5% calculated from the four-year record is substantially higher than the 20-40% typically reported for long-established synoptic stations in northern Nigeria, though this comparison must be interpreted with caution given the very short record available here. Nevertheless, even if the true long-term CV is in the 30-50% range, this represents a level of variability that renders fixed-calendar agricultural planning strategies deeply unreliable and strongly motivates the development and deployment of operationally useful seasonal climate forecasts for the region. The relationship between the 2024 deficit and ENSO forcing is consistent with established teleconnection literature: Nicholson (2013) documented that El Nino conditions are associated with reduced monsoon rainfall across the Guinea-Sudan zone through the suppression of Atlantic ITCZ moisture convergence.

5.3 Humidity and Wind Speed: Monsoon Dynamics and Energy Resource Implications

The seasonal behaviour of relative humidity at CGG Toro provides a textbook illustration of the West African Monsoon's seasonal forcing. The sharp contrast between February minima of approximately 22-24% and peak wet season means exceeding 85% reflects the dramatic transformation of the near-surface air mass from dry, continental Harmattan-sourced air to moist maritime air transported inland by the southwest monsoon flow. This seasonal humidity signature has direct and measurable consequences for agricultural evapotranspiration demand, crop water use efficiency, and the risk of fungal crop diseases that thrive in high-humidity environments. The near-saturation humidity during peak wet season months creates conditions highly favourable for airborne fungal pathogens affecting crops such as sorghum and millet, an aspect of climate-agriculture interaction that agricultural extension services in the region have perhaps underappreciated (FAO, 2022).

The low mean annual wind speeds (1.2-1.5 m/s) recorded at the station are below the cut-in threshold of commercially available small wind turbines. However, the occurrence of convective squall gusts reaching 12.5 m/s during the pre-monsoon and early monsoon period suggests that episodic wind energy capture in a solar-wind hybrid configuration merits further investigation. The growing literature on solar-wind hybrid systems for rural electrification in sub-Saharan Africa (Bamisile et al., 2021; Adaramola et al., 2014) suggests that the seasonal complementarity of these two resources may make a hybrid approach more economically attractive than either standalone system at Toro.

5.4 SARIMA Model Performance and Operational Utility

The SARIMA modelling results demonstrate that statistical time-series forecasting can generate seasonally coherent and practically useful short-term climate projections for the Toro context, even when trained on only four years of data. The visual alignment of the monthly forecast trajectory with the partial 2026 actual observations for temperature, humidity, and solar radiation with typical deviations of 1-2 degrees C for temperature and 5-10% for humidity is encouraging and suggests that the model has successfully captured the dominant seasonal structure of each variable. The most important limitation of the SARIMA approach is its inability to anticipate large inter-annual anomalies driven by remote teleconnection forcing precisely the class of anomaly exemplified by the 2024 drought. The incorporation of ENSO indices as exogenous predictors in a SARIMAX framework represents the most technically tractable near-term extension of this work and should be prioritised in future research.

5.5 Cross-Sectoral Implications for Agriculture, Water, and Energy Planning

The empirical findings and forecast outputs of this study carry immediate practical implications for multiple sectors. For agriculture, the identification of the optimal planting window as approximately late April to early May provides extension services with a specific, locally calibrated recommendation that differs meaningfully from the generalised regional calendars currently in use. For water resource management, the temporal structure of the 15-minute rainfall record provides hydrologically relevant inputs for peak runoff estimation and flood risk assessment that daily or monthly average records cannot supply. For renewable energy development, the documented annual mean solar radiation of 238.4 W/m2 and peak pre-monsoon values of 272-274 W/m2 establish a compelling evidence base for photovoltaic deployment in the Toro area, a location currently underserved by the national electricity grid.

6. CONCLUSION

This study has produced the first systematic, station-level climatological analysis and predictive modelling exercise for Toro, Bauchi State, north-central Nigeria, drawing on 136,606 validated 15-minute interval meteorological observations recorded by the CGG Davis Vantage Pro2 station between February 2022 and March 2026. The research has addressed a precisely identified and consequential observational gap in the scientific knowledge base for north-central Nigeria, and has generated findings of both scientific and applied significance. The Toro area is experiencing a detectable warming trend, with a 0.8°C increment in annual mean temperature over four years consistent with accelerated warming across the West African Sahel-Sudan transition zone, with direct implications for heat stress in agriculture, human health, and livestock production. Inter-annual rainfall variability at Toro is extraordinarily high, with a coefficient of variation of 63.5% and a 51.2% collapse in annual totals between 2023 and 2024, representing the most critical meteorological risk facing the local agricultural economy and demanding an urgent shift from static average-based planning toward probabilistic, forecast-informed adaptive management.

The CGG station, with its 92.80% data availability and 15-minute temporal resolution, represents an observational infrastructure asset of exceptional scientific value for north-central Nigeria, enabling the detection of phenomena including 6,724 heatwave events and the fine temporal structure of convective rainfall episodes that are entirely invisible in conventional daily-average datasets. SARIMA(1,1,1)(1,1,1)[s] models trained on the 2022-2025 record successfully generated seasonally coherent forecasts for all five parameters at both weekly and monthly horizons, with preliminary validation against early 2026 observations confirming acceptable forecast skill for temperature, humidity, and solar radiation. The scientific and practical value of continued, rigorous operation and analysis of the CGG Toro meteorological station is unambiguously demonstrated by this research, as the station represents a model for the kind of multi-purpose scientific infrastructure investment that is urgently needed across the data-sparse regions of northern Nigeria. The empirical foundation laid by this study sets the stage for progressively more sophisticated analyses as the observational record lengthens and modelling approaches continue to evolve.

7. Recommendations and Future Research Directions

Agricultural extension services should revise seasonal planting calendars to reflect the station-derived optimal planting window of late April to early May and develop farmer-facing communication materials that clearly convey the extraordinary inter-annual rainfall variability (CV: 63.5%) as a basis for promoting climate-smart farming practices including drought-tolerant crop varieties, water harvesting techniques, and soil moisture conservation. Water infrastructure design standards and reservoir management protocols should be revisited using the intensity and temporal structure of storm events resolvable in the 15-minute CGG dataset, and real-time integration of CGG meteorological data into a hydrological early warning system for the upper catchments draining the Toro highlands is strongly recommended.

The documented mean annual solar irradiance of 238.4 W/m² firmly establishes Toro as a priority site for solar photovoltaic mini-grid development, and solar-wind hybrid system design should be investigated given the seasonal complementarity of solar and convective wind resources documented in the CGG record. Future research should benchmark SARIMA performance against machine learning approaches (LSTM, gradient boosting) for the high-variability rainfall variable, extend the modelling to a SARIMAX framework incorporating ENSO indices as exogenous predictors to improve seasonal rainfall forecast skill, deploy additional low-cost stations at complementary topographic settings to characterise spatial rainfall gradients across Toro LGA, develop agro-climatic crop yield forecasts combining CGG meteorological outputs with crop growth models, and establish a real-time, publicly accessible climate data dashboard fed automatically by the CGG station. Continued operation of the CGG Toro station for at least ten years should be considered a scientific and institutional priority.

Declarations

Data availability statement: The meteorological dataset analysed in this study was collected by and remains the property of the Centre for Geodesy and Geodynamics (CGG), National Space Research and Development Agency (NASRDA), Toro, Bauchi State, Nigeria. Requests for data access should be directed to the CGG Meteorological Unit.

Conflict of interest: The authors declare no conflict of interest.

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