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Remote Sensing-Based Assessment of Hydro-Climatic Variability and Spatial Drought–Extreme Rainfall Conditions in the Transboundary Tano River Basin, West Africa

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Abstract

Hydro-climatic variability affects water management, ecosystems, and climate-risk planning in tropical basins. This study examined rainfall, rainfall extremes, dry spells, vegetation greenness, land surface temperature, and spatial drought–extreme-rainfall conditions in the Tano River Basin during 2000–2024. CHIRPS rainfall and Landsat observations were processed in Google Earth Engine to derive annual rainfall, maximum 1-day rainfall (Rx1day), maximum 5-day rainfall (Rx5day), consecutive dry days (CDD), NDVI, and land surface temperature (LST). Modified Mann–Kendall/Sen’s slope and Spearman correlation assessed trends and associations. Entropy-weighted Drought Condition Index (DCI) and Extreme Rainfall Potential Index (ERPI) distinguished drought-related conditions from extreme rainfall potential.

Annual rainfall, Rx1day, Rx5day, CDD, and LST showed no significant monotonic trends. Rainfall had a positive Sen’s slope of 1.944 mm year⁻¹ ($p = 0.726$), whereas NDVI increased significantly by 0.00285 year⁻¹ ($p = 0.001$). Rainfall correlated positively with Rx1day ($\rho = 0.524$, $p = 0.007$) and Rx5day ($\rho = 0.467$, $p = 0.019$), while vegetation and temperature relationships were weak and non-significant. CDD had the greatest DCI weight (0.324), whereas Rx1day had the greatest ERPI weight (0.398). Sensitivity analysis confirmed stable rankings under equal weighting and $\pm 20\%$ weight perturbations. CHIRPS showed monthly agreement with GPM IMERG ($R^2 = 0.881$; RMSE = 27.96 mm; MAE = 18.56 mm). Spatial analysis identified drought-dominant and extreme-rainfall-dominant zones, with limited compound stress. The framework supports adaptation planning.

Keywords: Hydro-climatic variability; Extreme rainfall; Consecutive dry days; Drought Condition Index; Extreme Rainfall Potential Index; Entropy weighting; CHIRPS; Landsat; Tano River Basin.

1. Introduction

Hydro-climatic variability has become a defining feature of environmental change, with important implications for water resources, ecosystem functioning, agricultural production, and socio-

economic resilience, particularly in climate-sensitive regions such as sub-Saharan Africa (Intergovernmental Panel on Climate Change, 2021; World Bank, 2022). Rising temperatures can intensify the hydrological cycle by increasing atmospheric moisture demand and altering the timing, intensity, and distribution of rainfall events. These changes can occur alongside prolonged dry spells and short-duration high-intensity rainfall, thereby increasing the complexity of water-related hazards within the same landscape (Trenberth, 2011; Donat et al., 2016; Dosio et al., 2021). Such conditions are especially important in river basins where rainfall deficits, vegetation stress, dry-spell persistence, and extreme rainfall events can affect water availability and runoff generation through different pathways.

West Africa is highly vulnerable to hydro-climatic variability because rainfall is strongly influenced by the seasonal migration of the Intertropical Convergence Zone, land–atmosphere interactions, and regional circulation systems (Nicholson, 2013; Sylla et al., 2016). Historical climate records show that the region has experienced severe drought episodes, partial rainfall recovery, and continuing rainfall variability during recent decades. In many locations, annual rainfall totals may remain relatively stable while rainfall timing, rainfall intensity, and dry-spell characteristics change substantially (Nicholson et al., 2018; Panthou et al., 2018; Taylor et al., 2017). These changes influence runoff, soil-moisture availability, evapotranspiration, vegetation condition, and the occurrence of water-related hazards (Trenberth, 2011; Donat et al., 2016).

In Ghana, hydro-climatic variability is expressed through marked spatial differences in rainfall distribution, vegetation condition, temperature, and land-surface characteristics. These variations have important implications for agriculture, domestic water supply, ecosystem functioning, and watershed management (World Bank, 2022; Sultan & Gaetani, 2016). The Tano River Basin, located within the humid tropical zone of southwestern Ghana, experiences a bimodal rainfall regime but is also affected by changing rainfall timing, land-use transformation, forest loss, agricultural expansion, and increasing pressure on natural resources. These factors can alter surface energy balance, infiltration, runoff generation, and vegetation response, thereby influencing both drought-related and extreme-rainfall-related conditions within the basin (Serdeczny et al., 2017; Sultan & Gaetani, 2016).

Previous studies of hydro-climatic variability in West Africa have often examined rainfall trends, temperature change, vegetation dynamics, drought conditions, or flood-related rainfall extremes separately (Sylla et al., 2016; Panthou et al., 2018). Although such studies provide valuable information, separate analyses of individual indicators may not adequately represent the coexistence of rainfall deficits, prolonged dry spells, vegetation conditions, thermal conditions, and intense rainfall events within a single river basin. In particular, the use of one composite drought–flood index may obscure whether high hydro-climatic stress is driven mainly by rainfall deficit, dry-spell persistence, vegetation deficit, thermal conditions, or short-duration rainfall extremes. This limitation is important because

drought-related processes and extreme-rainfall processes do not necessarily occur simultaneously or follow the same spatial pattern.

Recent advances in Earth Observation provide a valuable basis for addressing these limitations. Satellite datasets can support consistent long-term monitoring across data-scarce basins and allow rainfall, vegetation, and land-surface thermal conditions to be assessed within a common analytical framework (Gorelick et al., 2017). CHIRPS rainfall data have been widely used to monitor rainfall variability across Africa because they combine satellite infrared observations with station information and provide long-term spatially continuous coverage (Funk et al., 2015; Beck et al., 2020). Landsat imagery provides suitable observations for deriving vegetation indices and land surface temperature, thereby supporting assessment of vegetation greenness and surface thermal conditions over time (Roy et al., 2014; Ermida et al., 2020). In addition, ETCCDI rainfall indices, including maximum 1-day rainfall, maximum 5-day rainfall, and consecutive dry days, provide standard measures of short-duration rainfall intensity, multi-day rainfall accumulation, and dry-spell persistence (Alexander et al., 2006; Zhang et al., 2011).

Despite these advances, several methodological gaps remain. First, limited studies distinguish drought-related conditions from extreme-rainfall potential while integrating rainfall, rainfall extremes, vegetation, and thermal indicators within one basin-scale framework. Second, many composite hydro-climatic indices apply equal weighting to all indicators, although the contribution and variability of rainfall deficit, dry spells, vegetation condition, land surface temperature, and rainfall extremes may differ. Third, the spatial distribution of drought-related and extreme-rainfall-related conditions is often concealed when only basin-average values are examined. Finally, satellite rainfall products are frequently assessed using a single comparison dataset, whereas comparison with another rainfall product can provide useful evidence of cross-product consistency in regions with limited gauge coverage (Satgé et al., 2020; Dinku et al., 2018; Huffman et al., 2020).

This study addresses these gaps by developing a revised remote-sensing framework for assessing hydro-climatic variability and spatial drought–extreme-rainfall conditions in the Tano River Basin between 2000 and 2024. The framework integrates annual rainfall, Rx1day, Rx5day, CDD, NDVI, and LST. Rather than combining all variables into one equal-weight drought–flood index, the study develops separate entropy-weighted indices. The Drought Condition Index integrates rainfall deficit, consecutive dry days, land surface temperature, and vegetation deficit, whereas the Extreme Rainfall Potential Index integrates annual rainfall, Rx1day, and Rx5day. This separation makes it possible to identify drought-dominant and extreme-rainfall-dominant conditions independently before examining their localised spatial overlap.

The study therefore aims to assess hydroclimatic variability and spatial drought–extreme rainfall conditions in the Tano River Basin from 2000 to 2024. It evaluates temporal trends in rainfall,

rainfall extremes, dry spells, vegetation greenness, and land surface temperature; examines statistical associations among hydro-climatic variables; develops entropy-weighted drought and extreme-rainfall indices; evaluates the sensitivity of the indices to alternative weighting schemes; maps relative spatial hydro-climatic conditions for selected years; and assesses monthly CHIRPS–IMERG rainfall agreement. Through this framework, the study provides a transparent approach for identifying the distinct and spatially variable hydro-climatic processes that influence climate-risk conditions in tropical river basins.

2. Methodology

2.1 Study Area

The Tano River Basin is located in southwestern Ghana, forming part of a transboundary hydrological system within the humid tropical zone of West Africa. The basin is influenced by the seasonal migration of the Intertropical Convergence Zone, which controls the timing and spatial distribution of rainfall across the region (Nicholson, 2018). The climate is characterised by a bimodal rainfall regime, with major and minor rainy seasons generally occurring between April and July and between September and October, respectively. Mean annual rainfall commonly ranges from approximately 1,200 mm to 1,800 mm, while temperatures remain relatively high throughout the year because of strong solar radiation and tropical atmospheric conditions (IPCC, 2021).

The basin supports agricultural production, settlements, forest ecosystems, water-resource systems, and biodiversity conservation. However, deforestation, agricultural expansion, settlement growth, and other land-use pressures have altered land-surface conditions and may influence runoff generation, surface energy balance, vegetation response, and local hydrological processes. These environmental pressures, together with rainfall variability and dry-spell occurrence, make the basin suitable for assessing drought-related conditions and extreme-rainfall potential within a common hydro-climatic framework.

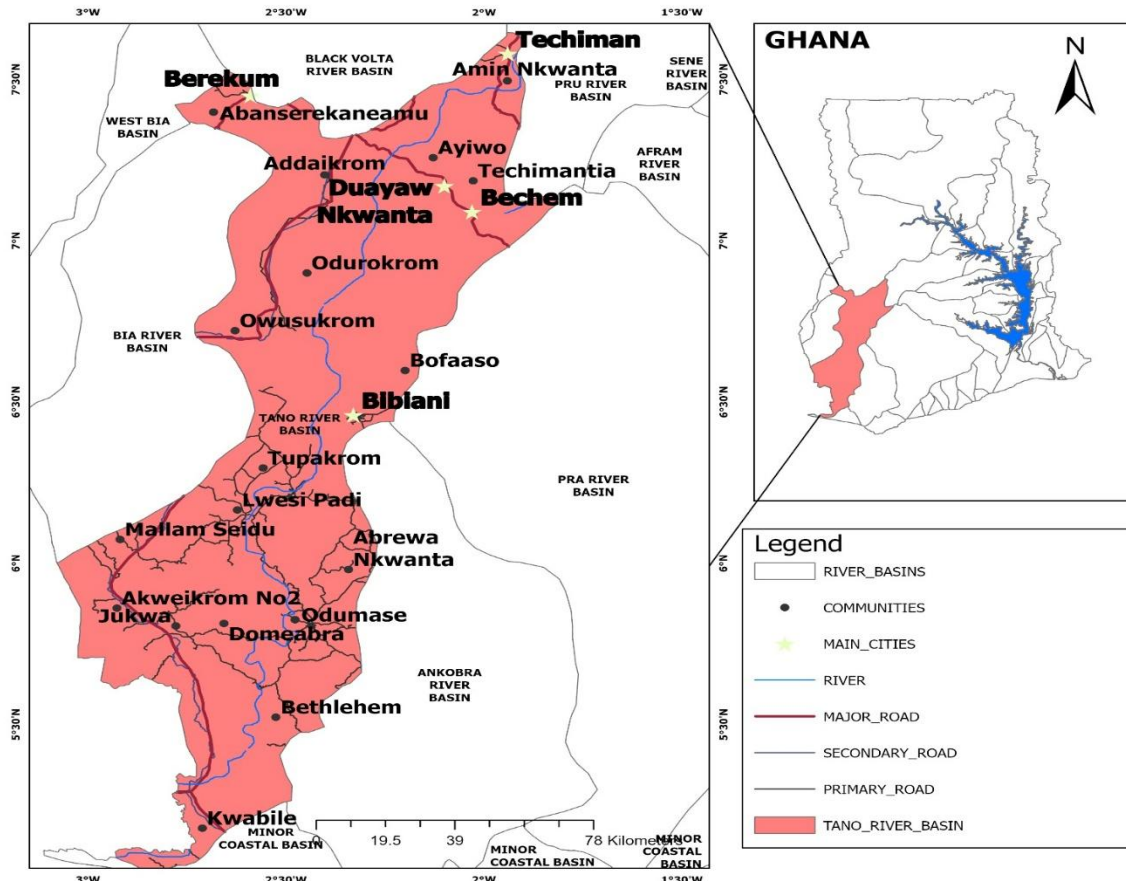


Figure 1. Location of the Tano River Basin in West Africa, showing its position within Ghana. The map illustrates the basin boundary, river network, elevation, and key settlements, providing the geographical context for the hydro-climatic analysis.

2.2 Data Sources

The study integrated CHIRPS daily rainfall, Landsat Collection 2 Level-2 imagery, and GPM IMERG monthly rainfall data to assess hydro-climatic variability between 2000 and 2024. CHIRPS was used to derive annual rainfall, maximum 1-day rainfall, maximum 5-day rainfall, and consecutive dry days. Landsat imagery was used to derive annual NDVI and LST composites. GPM IMERG was used to assess the monthly consistency of CHIRPS rainfall estimates.

CHIRPS provides quasi-global rainfall estimates at approximately 0.05° spatial resolution and combines satellite infrared observations with station information, making it suitable for hydro-climatic assessment in regions with uneven gauge coverage such as West Africa (Funk et al., 2015; Beck et al., 2020). Landsat Collection 2 Level-2 products provide surface-reflectance and surface-temperature observations at 30 m spatial resolution, allowing consistent long-term assessment of vegetation greenness and land-surface thermal conditions (Roy et al., 2014; Ermida et al., 2020). GPM IMERG provides satellite-derived rainfall estimates at approximately 0.10° spatial resolution and was used to evaluate cross-product agreement with CHIRPS rainfall data (Huffman et al., 2023).

145 **Table 1. Summary of datasets used in the study.**

Dataset	Source	Spatial resolution	Temporal coverage	Application
CHIRPS Daily Rainfall	Climate Hazards Centre	0.05°	2000–2024	Annual rainfall, Rx1day, Rx5day, and CDD
Landsat Collection 2 Level-2	USGS	30 m	2000–2024	NDVI and LST
GPM IMERG Monthly	NASA	Approximately 0.10°	2001–2024	CHIRPS–IMERG rainfall agreement
Tano River Basin boundary	Basin vector dataset	Vector	Not applicable	Spatial masking and grid-based analysis

146 2.3 Data Preprocessing

147 All datasets were processed in Google Earth Engine, which provides a cloud-based
 148 environment for reproducible processing of large geospatial datasets (Gorelick et al., 2017). CHIRPS
 149 and Landsat observations were clipped to the Tano River Basin boundary and filtered to the 2000–2024
 150 study period. CHIRPS daily rainfall was aggregated to annual totals and used to derive rainfall-extreme
 151 indices. Landsat images were filtered using the QA_PIXEL and QA_RADSAT bands to remove cloud-
 152 contaminated, cloud-shadow, fill, and radiometrically saturated pixels.

153 Annual Landsat composites were created using median values from valid observations within
 154 each year. The use of annual median composites reduced residual atmospheric noise and minimised the
 155 influence of isolated poor-quality scenes (Ermida et al., 2020). Landsat 5 TM and Landsat 7 ETM+
 156 imagery were used during the early part of the study period, whereas Landsat 8 OLI/TIRS and Landsat
 157 9 OLI-2/TIRS-2 imagery was used in later years. Annual NDVI and LST values were subsequently
 158 calculated across the basin.

159 For spatial analysis, raw annual rainfall, Rx1day, Rx5day, CDD, NDVI, and LST values were
 160 summarised within a 0.10° analysis grid covering the basin. Grid cells were clipped to the basin
 161 boundary before analysis. This approach was adopted to avoid false spatial precision because rainfall
 162 data are available at a substantially coarser spatial resolution than Landsat imagery.

163 2.4 Rainfall Analysis

164 Annual rainfall was calculated by summing daily CHIRPS rainfall values for each year:

$$R_{\text{annual}} = \sum_{i=1}^n R_i \quad (1)$$

where R_i represents daily rainfall in millimetres and n represents the number of days in a given year. Annual rainfall provided an indicator of total precipitation input and supported assessment of interannual rainfall variability within the basin (Funk et al., 2015).

2.5 Extreme Rainfall Indices

Extreme rainfall characteristics were quantified using indices defined by the Expert Team on Climate Change Detection and Indices framework. Maximum 1-day rainfall was calculated as:

$$Rx1day = \max(R_i) \quad (2)$$

Maximum 5-day rainfall was calculated as:

$$Rx5day = \max\left(\sum_{i=j}^{j+4} R_i\right) \quad (3)$$

Consecutive dry days were calculated as the longest sequence of days with rainfall below 1 mm:

$$CDD = \max(d_i \mid R_i < 1 \text{ mm}) \quad (4)$$

$Rx1day$ represents the maximum daily rainfall intensity within a year, whereas $Rx5day$ captures the maximum accumulated rainfall over five consecutive days. CDD represents annual dry-spell persistence. Together, these indicators provide complementary information on rainfall intensity, short-period accumulation, and dry conditions relevant to hydro-climatic assessment (Alexander et al., 2006; Zhang et al., 2011; Sun et al., 2021).

2.6 Vegetation Analysis

Vegetation condition was assessed using the Normalised Difference Vegetation Index:

$$NDVI = \frac{NIR - RED}{NIR + RED} \quad (5)$$

where NIR and RED represent near-infrared and red surface-reflectance values, respectively. $NDVI$ values generally range from -1 to $+1$, with higher values representing greener vegetation conditions. Annual median $NDVI$ composites were used to reduce the effects of cloud contamination and individual scene anomalies (Tucker, 1979).

2.7 Land Surface Temperature

Land surface temperature was derived from the Landsat Collection 2 Level-2 surface-temperature band using the USGS scaling parameters:

$$LST = (DN \times 0.00341802 + 149.0) - 273.15 \quad (6)$$

where DN represents the scaled surface-temperature pixel value. The resulting values were expressed in degrees Celsius. LST was included as an indicator of surface thermal conditions that may influence evapotranspiration, vegetation moisture, and drought-related stress (Ermida et al., 2020).

2.8 Trend Analysis

Temporal trends in annual rainfall, Rx1day, Rx5day, CDD, NDVI, and LST were assessed using the modified Mann–Kendall test with the Hamed–Rao variance correction. The Mann–Kendall test is a non-parametric approach suitable for hydro-climatic time series that may not satisfy normality assumptions, while the Hamed–Rao correction reduces the influence of serial correlation on trend inference (Mann, 1945; Kendall, 1975; Hamed & Rao, 1998).

The Mann–Kendall statistic was expressed as:

$$S = \sum_{i=1}^{n-1} \sum_{j=i+1}^n \text{sgn}(x_j - x_i) \quad (7)$$

where x_i and x_j represent observations at times i and j , respectively. The magnitude of monotonic change was estimated using Sen's slope (Sen, 1968):

$$\beta = \text{median}\left(\frac{x_j - x_i}{j - i}\right), j > i \quad (8)$$

Positive slopes indicate increasing trends, whereas negative slopes indicate decreasing trends. Statistical significance was assessed at the 0.05 level.

2.9 Correlation Analysis

Relationships among annual rainfall, Rx1day, Rx5day, CDD, NDVI, and LST were assessed using Spearman's rank correlation. Spearman correlation was selected because it measures monotonic associations without requiring normally distributed variables (Spearman, 1904).

$$\rho = 1 - \frac{6\sum d_i^2}{n(n^2 - 1)} \quad (9)$$

where d_i represents the difference between paired ranks and n represents the number of paired observations. Correlations were interpreted as statistical associations rather than direct evidence of causality.

2.10 Entropy-Weighted Drought Condition Index and Extreme Rainfall Potential Index

The revised framework separated drought-related conditions from extreme-rainfall potential. All annual basin-average indicators were first normalised to values between zero and one. For indicators of increased hydro-climatic stress, standard min–max normalisation was used:

$$x'_{ij} = \frac{x_{ij} - \min(x_j)}{\max(x_j) - \min(x_j)} \quad (10)$$

For rainfall and NDVI, which reduce drought-related stress when values are high, reverse normalisation was used:

$$x'_{ij} = \frac{\max(x_j) - x_{ij}}{\max(x_j) - \min(x_j)} \quad (11)$$

Entropy weighting was applied to reduce subjectivity in assigning indicator weights. The normalised proportion of the indicator j in year i was calculated as:

$$p_{ij} = \frac{x'_{ij} + \varepsilon}{\sum_{i=1}^n (x'_{ij} + \varepsilon)} \quad (12)$$

where ε is a small constant added to prevent logarithms of zero. Entropy was then calculated as:

$$e_j = -\frac{1}{\ln(n)} \sum_{i=1}^n p_{ij} \ln(p_{ij}) \quad (13)$$

The degree of diversification was calculated as:

$$d_j = 1 - e_j \quad (14)$$

The entropy weight (Shannon, 1948) of each indicator was calculated as:

$$w_j = \frac{d_j}{\sum_{j=1}^m d_j} \quad (15)$$

The Drought Condition Index was calculated as:

$$DCI = w_1 R_d + w_2 CDD_n + w_3 LST_n + w_4 NDVI_d \quad (16)$$

where R_d represents rainfall deficit, CDD_n represents normalised consecutive dry days, LST_n represents normalised land surface temperature, and $NDVI_d$ represents vegetation deficit.

The Extreme Rainfall Potential Index was calculated as:

$$ERPI = w_1 R_n + w_2 Rx1day_n + w_3 Rx5day_n \quad (17)$$

where R_n , $Rx1day_n$, and $Rx5day_n$ represent normalised annual rainfall, maximum 1-day rainfall, and maximum 5-day rainfall, respectively. The use of separate indices allowed drought-related conditions and rainfall-related extreme potential to be interpreted independently rather than being merged into a single composite score.

2.11 Sensitivity Analysis and Spatial Hydro-Climatic Classification

Sensitivity analysis was undertaken to determine whether DCI and ERPI rankings were strongly influenced by the selected weighting scheme. First, entropy-weighted results were compared with equal-weight results. Second, each entropy weight was increased and decreased by 20%, after which all weights were rescaled to sum to one. Ranking stability was assessed using Spearman rank correlation between baseline entropy-weighted results and alternative weighting scenarios. Agreement in the three highest-condition years was also assessed.

Spatial DCI and ERPI were mapped for 2000, 2007, 2013, 2016, 2023, and 2024. These years were selected to represent contrasting drought-related and extreme-rainfall-related conditions. Within each selected year, grid-cell indicator values were normalised independently. DCI and ERPI values, therefore, represent relative spatial conditions within a selected year and should not be interpreted as direct absolute comparisons of index magnitude across years.

The 33rd and 67th percentiles of annual grid-cell DCI and ERPI values were used to classify each index into low, moderate, and high classes. High DCI and high ERPI classes were subsequently combined to identify moderate or relatively low stress, drought-dominant condition, extreme-rainfall-dominant condition, and compound hydro-climatic stress.

2.12 CHIRPS–IMERG Rainfall Agreement

2.12 Rainfall-Product Agreement and Station-Based Climatology Comparison

Monthly basin-average CHIRPS rainfall was compared with monthly basin-average GPM IMERG rainfall between 2001 and 2024. The comparison included 288 paired monthly observations. Because both datasets are satellite-derived rainfall products, this assessment was interpreted as cross-product agreement rather than independent validation.

In addition, CHIRPS seasonal rainfall climatology was compared with available Ghana Meteorological Agency (GMet) station data for Sunyani and Wenchi. Monthly climatological rainfall totals were calculated for January–December over the 2000–2024 period for each location. This comparison was used as a station-based assessment of whether CHIRPS reproduced the broad seasonal rainfall cycle observed at the two available locations. The comparison included 24 paired town-month climatology observations.

Agreement between CHIRPS and both comparison datasets was assessed using the Pearson correlation coefficient, coefficient of determination, root mean square error, mean absolute error, and bias:

$$RMSE = \sqrt{\frac{1}{n} \sum_{i=1}^n (y_i - \hat{y}_i)^2} \quad (18)$$

$$MAE = \frac{1}{n} \sum_{i=1}^n |y_i - \hat{y}_i| \quad (19)$$

$$Bias = \frac{1}{n} \sum_{i=1}^n (y_i - \hat{y}_i) \quad (20)$$

where y_i represents CHIRPS rainfall and $\hat{y}_i$ represents either IMERG rainfall or GMet station rainfall, depending on the comparison. These metrics were used to assess association strength, average error magnitude, and systematic differences between rainfall estimates (Huffman et al., 2020).

2.13 Methodological Framework

The methodological framework integrated multi-source data acquisition, preprocessing, indicator derivation, statistical analysis, entropy weighting, sensitivity assessment, spatial mapping, and rainfall-agreement assessment. CHIRPS and Landsat data were clipped to the Tano River Basin and processed to derive annual rainfall, rainfall extremes, dry spells, NDVI, and LST. Modified Mann–Kendall analysis and Sen’s slope were used to assess temporal trends, while Spearman correlation analysis evaluated associations among hydro-climatic variables.

Entropy-weighted DCI and ERPI were subsequently calculated and evaluated through sensitivity analysis. Selected years were mapped using a common grid to identify relative drought-dominant, extreme-rainfall-dominant, and compound hydro-climatic conditions. Rainfall estimates were further assessed through monthly CHIRPS–IMERG cross-product agreement and CHIRPS–GMet seasonal-climatology comparison at Sunyani and Wenchi.

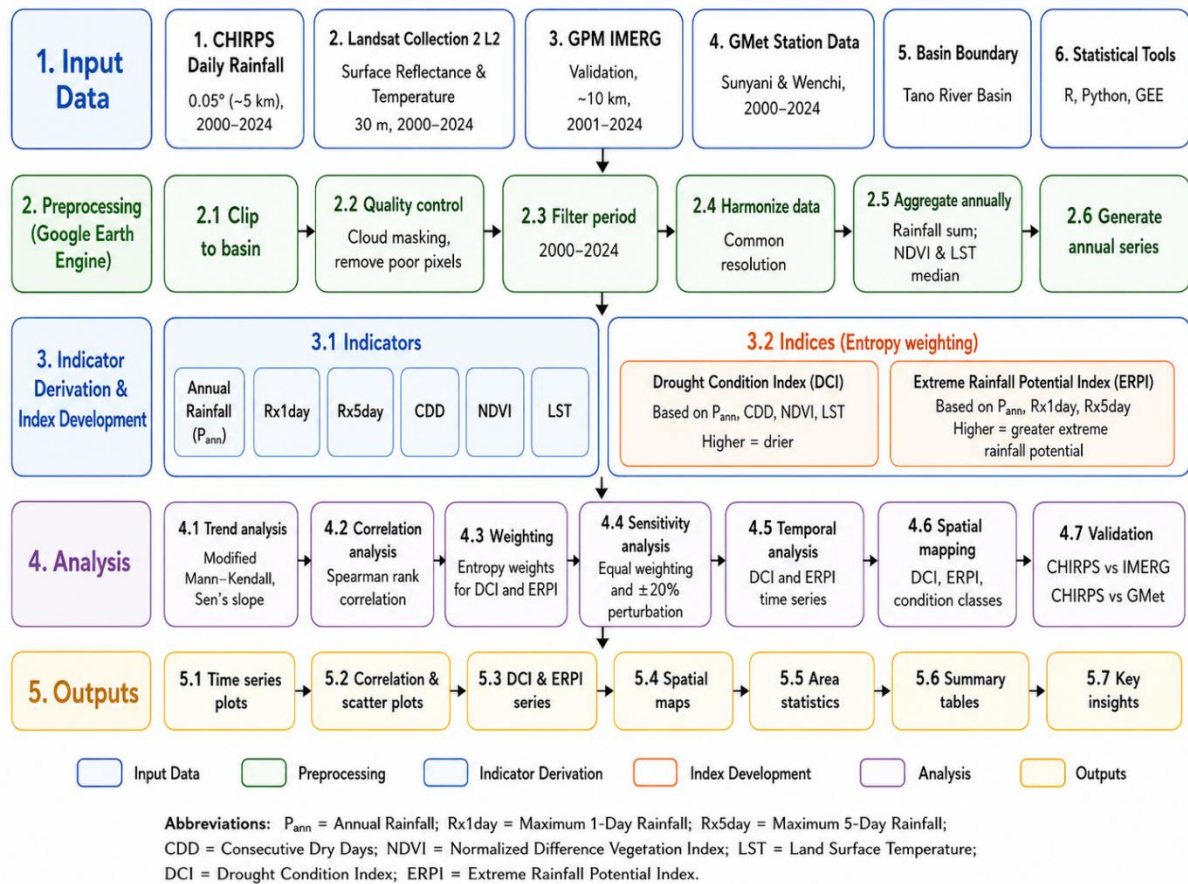


Figure 2. Methodological framework for hydro-climatic assessment in the Tano River Basin, showing multi-source data acquisition, preprocessing, annual indicator derivation, modified Mann–Kendall trend analysis, Spearman correlation analysis, entropy-weighted DCI and ERPI calculation, sensitivity analysis, spatial classification, CHIRPS–IMERG cross-product agreement, and CHIRPS–GMet seasonal-climatology comparison.

3.0 Results

3.1 Descriptive Characteristics of Hydro-Climatic Variables

Table 2 presents the descriptive statistics of annual rainfall, rainfall-extreme indices, consecutive dry days, NDVI, and LST in the Tano River Basin between 2000 and 2024. The results show substantial interannual variability in rainfall and rainfall-extreme indicators, whereas NDVI and LST exhibited relatively lower variability.

Annual rainfall had a mean value of 1441.96 mm, with a standard deviation of 174.74 mm and a coefficient of variation of 12.12%. Rainfall ranged from 1144.48 mm in 2013 to 1766.45 mm in 2007, showing clear differences between relatively dry and wet years. Rx1day had a mean value of 59.66 mm and ranged from 42.44 mm to 100.28 mm, while Rx5day had a mean value of 111.80 mm and ranged from 83.57 mm to 164.64 mm. The maximum Rx1day and Rx5day values both occurred in 2007,

indicating that this year experienced the strongest short-duration and five-day rainfall extremes within the study period.

CDD ranged from 24.85 to 44.68 days, with a mean value of 31.93 days. The longest basin-average dry spell occurred in 2024, whereas the shortest was recorded in 2006. NDVI had a mean of 0.672 and ranged from 0.533 to 0.747, indicating moderate but measurable year-to-year variation in basin-average vegetation greenness. LST had a mean value of 29.49°C and ranged from 26.52°C to 32.07°C.

Table 2. Descriptive statistics of hydro-climatic variables in the Tano River Basin, 2000–2024.

Variable	Mean	Standard deviation	Minimum	Median	Maximum	Coefficient of variation (%)
Rainfall (mm)	1441.96	174.74	1144.48	1388.44	1766.45	12.12
Rx1day (mm)	59.66	12.79	42.44	56.21	100.28	21.44
Rx5day (mm)	111.80	18.04	83.57	107.47	164.64	16.14
CDD (days)	31.93	4.58	24.85	30.59	44.68	14.34
NDVI	0.672	0.046	0.533	0.684	0.747	6.88
LST (°C)	29.49	1.25	26.52	29.39	32.07	4.22

3.2 Temporal Trends in Hydro-Climatic Variables

Figure 3 shows the temporal variation in annual rainfall, Rx1day, Rx5day, CDD, NDVI, and LST between 2000 and 2024. The corresponding modified Mann–Kendall and Sen’s slope results are presented in Table 3. Annual rainfall showed a weak positive Sen’s slope of 1.944 mm year⁻¹, but this trend was not statistically significant ($p = 0.726$). The rainfall series was therefore characterised mainly by interannual variability rather than a persistent directional increase or decrease.

Rx1day and Rx5day showed negative Sen’s slopes of –0.438 mm year⁻¹ and –0.430 mm year⁻¹, respectively. However, both trends were statistically non-significant. CDD showed a weak positive slope of 0.141 days year⁻¹, but this trend was also non-significant ($p = 0.216$). The results indicate that annual rainfall extremes and dry-spell duration varied considerably from year to year, but no statistically significant monotonic trend was detected over the 25 years.

NDVI was the only hydro-climatic variable with a statistically significant trend. The Sen's slope of $0.00285 \text{ year}^{-1}$ ($p = 0.001$) indicates a gradual increase in basin-average vegetation greenness. LST showed a positive slope of $0.043^\circ\text{C year}^{-1}$, but the trend was not statistically significant ($p = 0.168$). Therefore, the results do not provide sufficient evidence of a sustained basin-wide increase in LST during the study period.

Table 3. Modified Mann–Kendall trend analysis and Sen's slope estimates.

Variable	Kendall's tau	Sen's slope per year	p-value	Trend
Rainfall	0.053	1.944 mm	0.726	No significant trend
Rx1day	−0.233	−0.438 mm	0.107	No significant trend
Rx5day	−0.147	−0.430 mm	0.315	No significant trend
CDD	0.180	0.141 days	0.216	No significant trend
NDVI	0.473	0.00285	0.001	Significant increase
LST	0.200	0.043°C	0.168	No significant trend

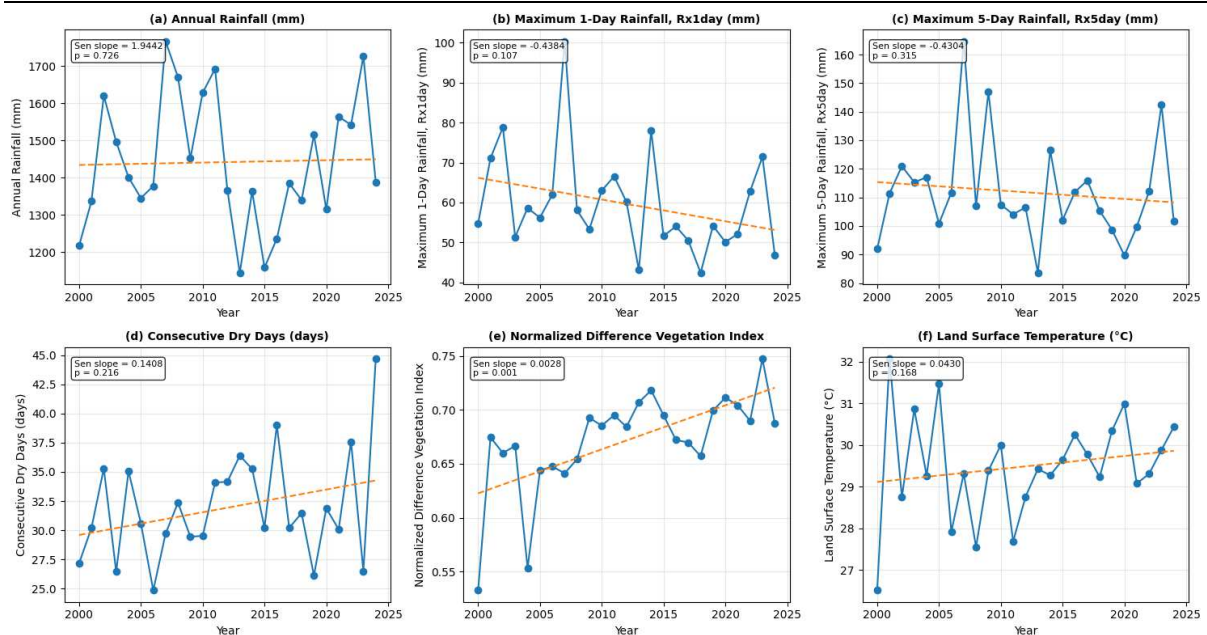


Figure 3. Hydro-climatic trends in the Tano River Basin between 2000 and 2024: (a) annual rainfall, (b) maximum 1-day rainfall, (c) maximum 5-day rainfall, (d) consecutive dry days, (e) normalised difference vegetation index, and (f) land surface temperature. Dashed lines represent visual linear fits, while statistical inference is based on modified Mann–Kendall results and Sen's slope estimates.

3.3 Annual Rainfall, Rainfall Extremes, and Dry-Spell Variability

The annual rainfall and rainfall-extreme series showed considerable temporal variation. The wettest year was 2007, when annual rainfall reached 1766.45 mm. This year also recorded the highest Rx1day value of 100.28 mm and the highest Rx5day value of 164.64 mm. The coincidence of high annual rainfall and strong rainfall extremes indicates that 2007 represented the most intense rainfall-related hydro-climatic condition in the time series.

Other relatively wet years included 2008, 2010, 2011, 2021, 2022, and 2023. However, high annual rainfall did not always correspond to identical rainfall-extreme conditions. For example, 2023 had high annual rainfall of 1725.87 mm and a high Rx5day value of 142.38 mm, but its Rx1day value was lower than the maximum observed in 2007.

The lowest annual rainfall occurred in 2013, when rainfall declined to 1144.48 mm. This year also recorded the lowest Rx1day value of 43.14 mm and the lowest Rx5day value of 83.57 mm. In contrast, the longest CDD value occurred in 2024, reaching 44.68 days, indicating that annual dry-spell persistence was particularly pronounced during that year. These results show that annual rainfall total, rainfall extremes, and dry-spell duration captured different aspects of hydro-climatic variability.

3.4 Vegetation and Land Surface Temperature Variability

NDVI showed an overall increasing pattern, although annual values fluctuated throughout the study period. The lowest NDVI value occurred in 2000 (0.533), whereas the highest value occurred in 2023 (0.747). The statistically significant positive NDVI trend indicates an increase in basin-average vegetation greenness between 2000 and 2024.

LST varied strongly between years, ranging from 26.52°C in 2000 to 32.07°C in 2001. Relatively high LST values were also recorded in 2005, 2019, 2020, and 2024. Although the overall Sen's slope was positive, the modified Mann–Kendall result was non-significant. Thus, LST should be interpreted as showing substantial interannual variability rather than a confirmed monotonic warming trend.

3.5 Hydro-Climatic Relationships and Rainfall-Product Agreement

Figure 4 presents the Spearman correlation matrix and CHIRPS–IMERG rainfall agreement. The correlation analysis showed that annual rainfall was significantly and positively associated with Rx1day. ($\rho = 0.524$, $p = 0.007$) and Rx5day ($\rho = 0.467$, $p = 0.019$). Rx1day and Rx5day were also significantly correlated. ($\rho = 0.551$, $p = 0.004$). These results indicate that years with higher annual rainfall generally experienced stronger daily and five-day rainfall extremes.

The relationship between annual rainfall and CDD was weak and non-significant ($\rho = -0.211$, $p = 0.312$). This result indicates that total annual rainfall did not fully explain the persistence of dry spells. NDVI showed no significant relationship with rainfall, rainfall extremes,

CDD, or LST. Similarly, LST showed weak and non-significant relationships with rainfall, Rx1day, Rx5day, and CDD. The positive association between NDVI and LST was weak and non-significant ($\rho = 0.261$, $p = 0.208$).

Monthly CHIRPS rainfall showed strong agreement with GPM IMERG rainfall between 2001 and 2024. The comparison included 288 paired monthly observations and produced a Pearson correlation coefficient of 0.939 and an R^2 value of 0.881. The regression slope was 1.030, with an intercept of 3.204 mm. RMSE was 27.96 mm, MAE was 18.56 mm, and bias was 6.66 mm. The positive bias indicates that CHIRPS produced slightly higher rainfall estimates than IMERG on average.

The clustering of observations around the regression line and the 1:1 line indicates that CHIRPS captured the main pattern of monthly rainfall variability represented by IMERG. However, this result represents cross-product agreement rather than independent validation because both datasets are satellite-derived rainfall products.

Table 4. CHIRPS–IMERG monthly rainfall agreement metrics, 2001–2024.

Metric	Value
Paired monthly observations	288
Pearson correlation coefficient	0.939
Coefficient of determination, R^2	0.881
Regression slope	1.030
Regression intercept	3.204 mm
RMSE	27.96 mm
MAE	18.56 mm
Bias	6.66 mm

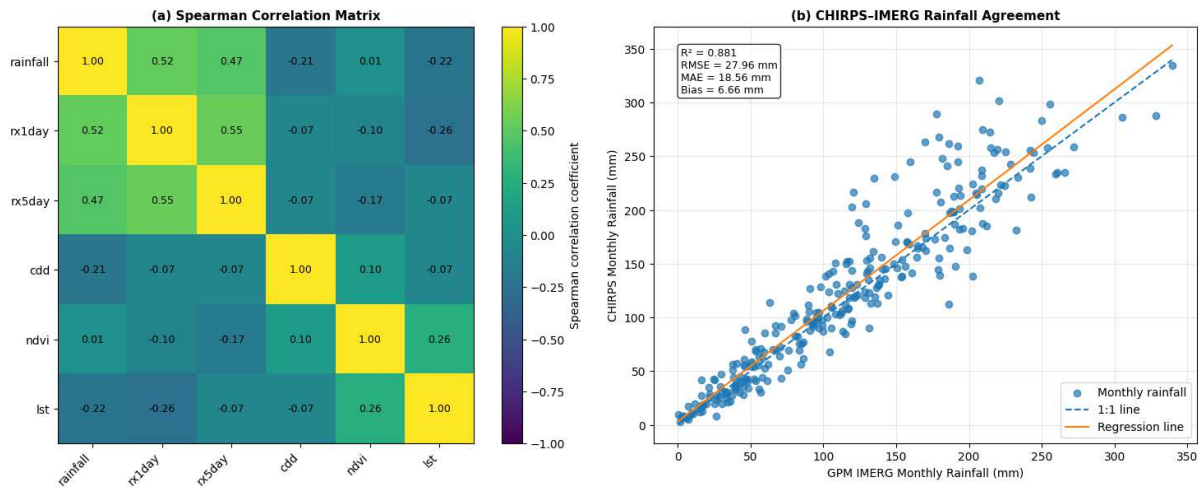


Figure 4. Hydro-climatic associations and rainfall-product agreement: (a) Spearman correlation matrix for annual rainfall, Rx1day, Rx5day, CDD, NDVI, and LST; and (b) monthly CHIRPS–IMERG rainfall agreement between 2001 and 2024.

3.6 Entropy Weights, Sensitivity Analysis, and Annual Hydro-Climatic Conditions

The entropy weights indicate that CDD made the largest contribution to the Drought Condition Index, with a weight of 0.324. Rainfall deficit and NDVI deficit contributed similar weights of 0.261 and 0.255, respectively, whereas LST had the lowest contribution to DCI, with a weight of 0.160. These results show that dry-spell persistence contained the greatest information contribution to annual drought-condition variability.

For ERPI, Rx1day had the highest entropy weight of 0.398, followed by annual rainfall with a weight of 0.303 and Rx5day with a weight of 0.299. This indicates that short-duration rainfall intensity contributed most strongly to the variability of extreme-rainfall potential. Sensitivity analysis showed that the annual rankings of DCI and ERPI remained highly stable under alternative weighting schemes. The Spearman rank correlation between entropy-weighted and equal-weight DCI was 0.975, while the corresponding ERPI value was 0.996. All $\pm 20\%$ weight-perturbation scenarios produced rank correlations above 0.990, and the three highest-condition years were retained under all tested weighting scenarios.

Figure 5a shows the temporal variation in DCI and ERPI, while Figure 5b presents the annual hydro-climatic classification. High DCI conditions occurred in 2000, 2001, 2004, 2005, 2013, 2015, 2016, and 2024. The highest DCI value occurred in 2024 (0.667), followed by 2016 (0.650), 2004 (0.630), and 2013 (0.582).

High ERPI conditions occurred in 2002, 2007, 2008, 2009, 2010, 2011, 2014, and 2023. The highest ERPI value was observed in 2007 (1.000), followed by 2023 (0.700) and 2002 (0.620). No year was classified as compound hydro-climatic stress at the annual basin-average scale. This indicates

that annual peaks in drought-related conditions and annual peaks in extreme-rainfall potential did not occur simultaneously at the basin-average level.

Table 5. Entropy weights and sensitivity-analysis summary.

Index	Indicator	Entropy weight
Drought Condition Index	Rainfall deficit	0.261
Drought Condition Index	Consecutive dry days	0.324
Drought Condition Index	Land surface temperature	0.160
Drought Condition Index	NDVI deficit	0.255
Extreme Rainfall Potential Index	Annual rainfall	0.303
Extreme Rainfall Potential Index	Rx1day	0.398
Extreme Rainfall Potential Index	Rx5day	0.299
Sensitivity comparison	Rank	Agreement in the three highest-condition correlation years
Entropy-weighted DCI versus equal-weight DCI	0.975	100%
Entropy-weighted ERPI versus equal-weight ERPI	0.996	100%
DCI under $\pm 20\%$ weight perturbation	≥ 0.990	100%
ERPI under $\pm 20\%$ weight perturbation	≥ 0.995	100%

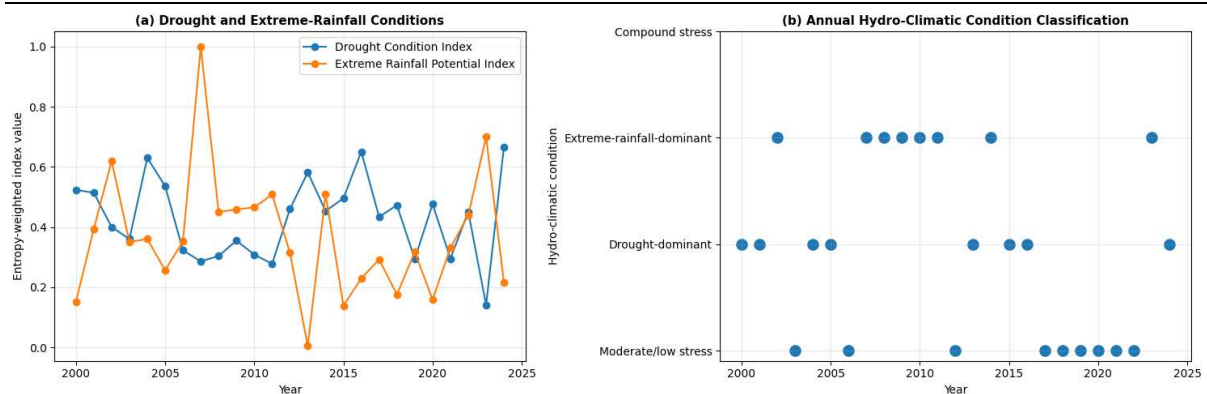


Figure 5. Drought conditions, extreme-rainfall potential, and annual hydro-climatic classification in the Tano River Basin between 2000 and 2024: (a) entropy-weighted Drought Condition Index and Extreme Rainfall Potential Index time series; and (b) annual drought-dominant, extreme-rainfall-dominant, and moderate or relatively low-stress conditions.

3.7 Spatial Distribution of the Drought Condition Index

Figure 6 shows the relative spatial distribution of DCI for 2000, 2007, 2013, 2016, 2023, and 2024. DCI values were normalised independently within each selected year. Therefore, the figure represents relative spatial drought conditions within a particular year and should not be interpreted as an absolute comparison of DCI magnitude between years.

The maps show a recurring north-to-south contrast in drought-related conditions. Relatively high DCI values were commonly observed across northern and central parts of the basin, whereas lower values were generally observed across southern grid cells. This pattern was particularly clear in 2013, 2016, and 2024. In 2024, relatively high DCI values covered broad northern and central areas, consistent with the highest annual basin-average DCI value recorded during the study period. The 2013 and 2016 maps also showed relatively high drought-condition values in northern sections of the basin, while southern areas generally showed lower relative drought conditions. The 2007 map showed comparatively lower drought-condition values across much of the basin, consistent with the high rainfall and rainfall-extreme conditions observed during that year.

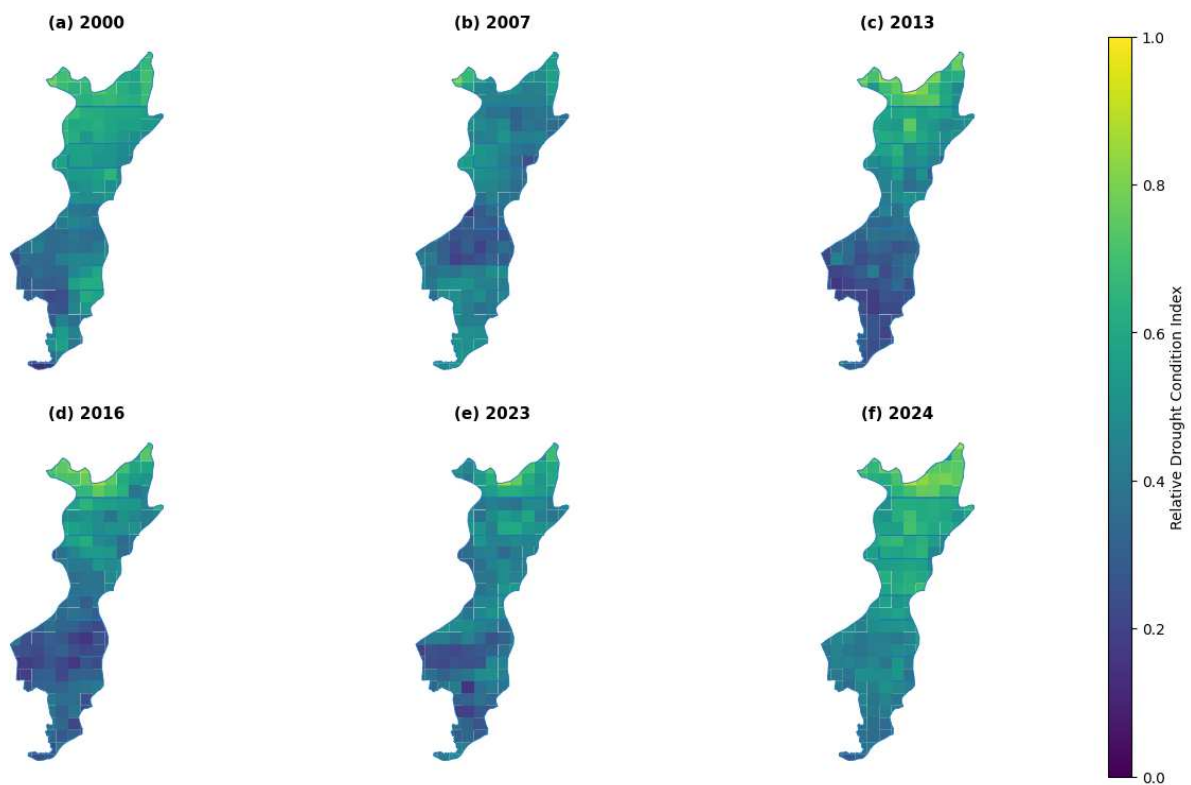


Figure 6. Relative spatial distribution of the Drought Condition Index in the Tano River Basin for selected years. Values were normalized independently within each year and represent relative drought-related conditions.

3.8 Spatial Distribution of Extreme Rainfall Potential

Figure 7 presents the relative spatial distribution of ERPI for the selected years. Similar to DCI, ERPI values were normalised independently for each year; consequently, the figure shows relative spatial extreme rainfall potential for each selected year. The spatial ERPI maps showed a general concentration of relatively high rainfall potential in southern and central parts of the basin. In 2007, extensive central and southern areas showed relatively high ERPI values, reflecting the high annual rainfall, Rx1day, and Rx5day values recorded that year. The southern concentration of ERPI was also evident in 2000, 2013, 2016, 2023, and 2024, although the size and intensity of these zones differed among years.

The northern part of the basin generally exhibited lower relative ERPI values, particularly in 2013, 2023, and 2024. These results suggest that short-duration and multi-day rainfall-extreme potential was spatially heterogeneous and was often stronger in southern and central grid cells.

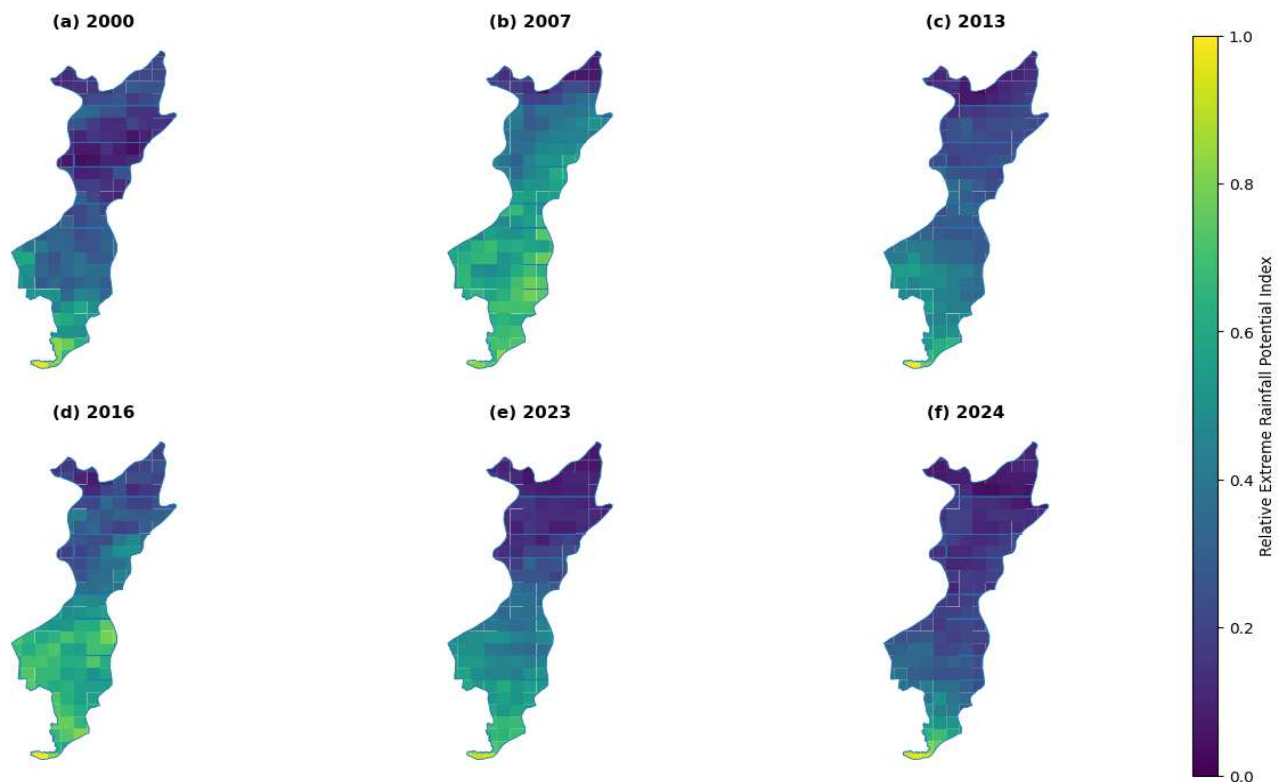


Figure 7. Relative spatial distribution of the Extreme Rainfall Potential Index in the Tano River Basin for selected years. Values were normalized independently within each year and represent relative extreme-rainfall potential.

3.9 Spatial Hydro-Climatic Condition Classes

Figure 8 combines the annual spatial DCI and ERPI classifications to identify moderate or relatively low stress, drought-dominant conditions, extreme-rainfall-dominant conditions, and compound hydro-climatic stress. The spatial condition classes show that drought-related and extreme-rainfall-related conditions occurred in different parts of the basin during the selected years.

In 2000, moderate or relatively low stress covered 41.40% of the mapped basin area, drought-dominant conditions covered 28.77%, and extreme-rainfall-dominant conditions covered 25.56%. Compound stress was mapped across 4.27% of the basin. In 2007, moderate or relatively low stress covered the largest proportion of the basin at 49.24%, while compound stress reached 8.24%, representing the highest compound-stress extent among the selected years. In 2013, drought-dominant conditions covered 34.27% of the mapped area, while extreme-rainfall-dominant conditions covered 31.86%. No compound stress was mapped in 2013. In 2016, drought-dominant and extreme-rainfall-dominant conditions covered 32.68% and 32.40%, respectively, while compound stress was absent.

In 2023, moderate or relatively low stress covered 37.88% of the basin, while drought-dominant and extreme-rainfall-dominant conditions covered 30.69% and 30.33%, respectively. Compound stress was present but occupied only 1.10% of the mapped basin area. In 2024, drought-dominant conditions covered 35.81% of the basin, representing the largest drought-dominant extent among the selected years. Extreme-rainfall-dominant conditions covered 31.60%, while no compound stress was mapped.

Table 6. Spatial area coverage of hydro-climatic condition classes.

Year	Moderate or relatively low stress (%)	Drought-dominant condition (%)	Extreme-rainfall-dominant condition (%)	Compound stress (%)
2000	41.40	28.77	25.56	4.27
2007	49.24	19.03	23.49	8.24
2013	33.87	34.27	31.86	0.00
2016	34.92	32.68	32.40	0.00
2023	37.88	30.69	30.33	1.10
2024	32.59	35.81	31.60	0.00

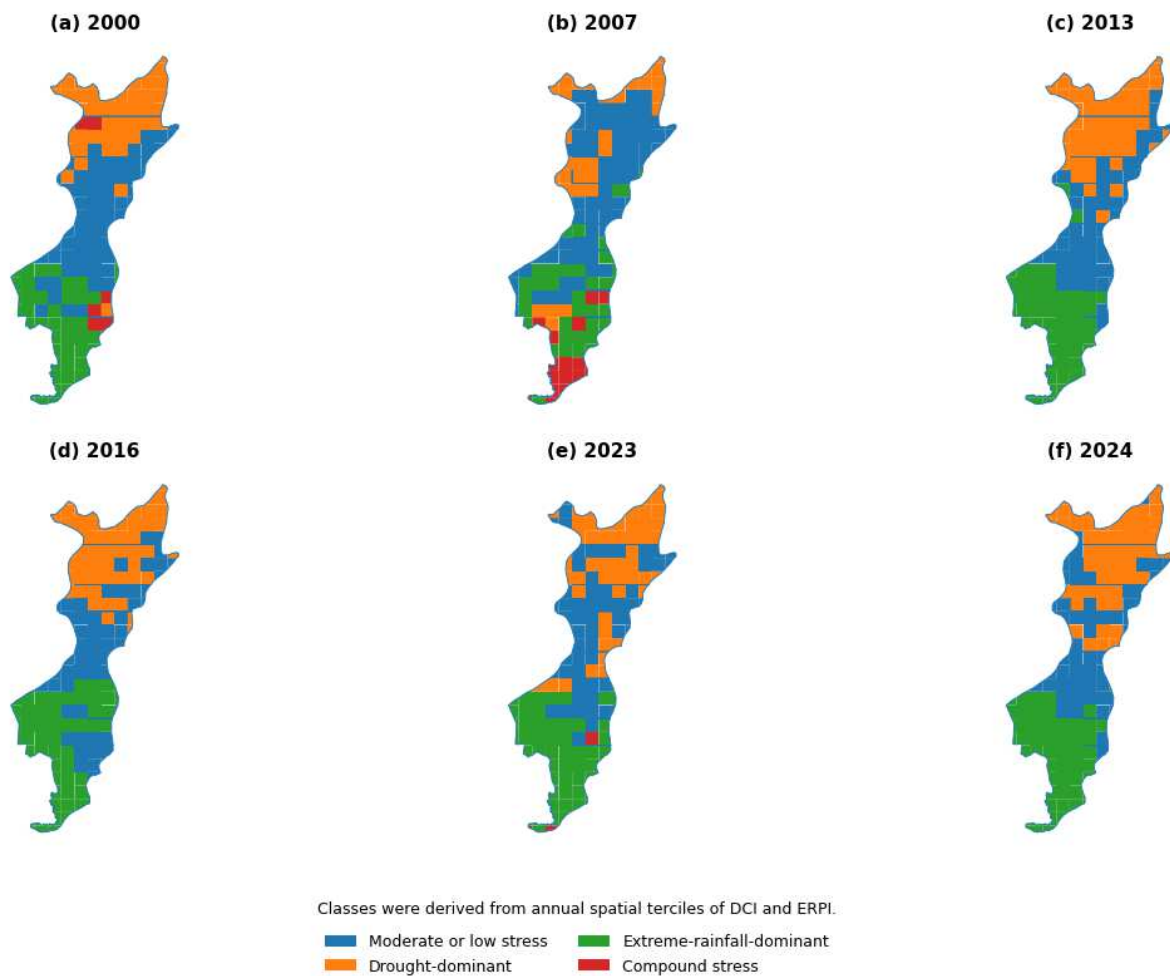


Figure 8. Spatial hydro-climatic condition classes in the Tano River Basin for selected years. Classes were derived from annual spatial terciles of DCI and ERPI.

3.10 Spatial Coverage of Hydro-Climatic Condition Classes

Figure 9 summarises the percentage area coverage of the four hydro-climatic condition classes. Moderate or relatively low-stress conditions represented the largest class in 2000, 2007, and 2023. In contrast, drought-dominant and extreme-rainfall-dominant conditions occupied nearly equal proportions of the basin in 2013, 2016, and 2024. The highest drought-dominant coverage occurred in 2024, when 35.81% of the mapped basin was classified as drought-dominant. The highest extreme-rainfall-dominant coverage occurred in 2013, reaching 31.86%. Compound hydro-climatic stress was limited to 2000, 2007, and 2023 and remained below 10% of the mapped basin in all selected years.

These results show that the basin rarely experienced widespread simultaneous drought-related and extreme-rainfall-related conditions. Instead, drought-dominant and extreme-rainfall-dominant conditions were generally separated spatially, with localised compound conditions appearing only in limited areas.

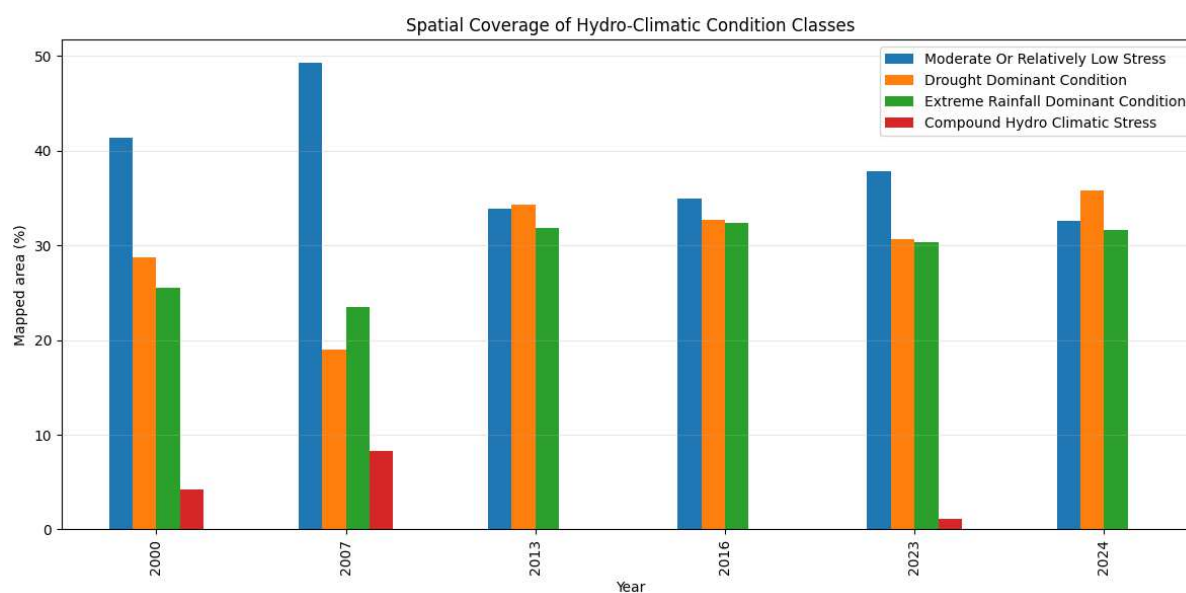


Figure 9. Percentage area coverage of moderate or relatively low stress, drought-dominant, extreme-rainfall-dominant, and compound hydro-climatic stress conditions across selected years.

3.11 CHIRPS–GMet Seasonal Climatology Agreement

The CHIRPS–GMet seasonal-climatology comparison provided a station-based assessment of whether CHIRPS reproduced the broad monthly rainfall pattern observed at Sunyani and Wenchi between 2000 and 2024. This analysis complemented the CHIRPS–IMERG comparison reported in Section 3.5. Whereas the CHIRPS–IMERG assessment evaluated agreement between two satellite-derived rainfall products using monthly basin-average data, the CHIRPS–GMet analysis compared long-term monthly rainfall climatology with available station observations.

The comparison included 24 paired town-month climatology observations derived from January–December average rainfall values for the two locations. Across the pooled dataset, CHIRPS showed a very strong positive association with GMet rainfall climatology ($r = 0.983, p < 0.001$), with a coefficient of determination of $R^2 = 0.966$ (Supplementary Figure S2). The regression slope of 0.917 indicated close correspondence between CHIRPS and GMet rainfall across the seasonal cycle.

The pooled RMSE and MAE were 14.80 mm and 11.16 mm, respectively, while the bias was -8.76 mm (Table 7). The negative bias indicates that CHIRPS slightly underestimated the GMet monthly rainfall climatology on average. At Sunyani, CHIRPS underestimated the pronounced June rainfall peak, whereas at Wenchi the agreement remained strong across most months, including the September–October rainfall maximum (Supplementary Figure S1). Despite these seasonal differences, both datasets showed a similar progression from low rainfall during December–February to increased rainfall during the major and minor rainy seasons.

Town-specific results also indicated strong agreement. Sunyani recorded $r = 0.983$, $R^2 = 0.966$, RMSE = 16.46 mm, MAE = 11.81 mm, and bias = -10.40 mm, while Wenchi recorded $r = 0.986$, $R^2 = 0.972$, RMSE = 12.93 mm, MAE = 10.51 mm, and bias = -7.12 mm (Table 7). These results support the suitability of CHIRPS for representing the broad seasonal rainfall structure across the selected locations near the Tano River Basin. However, because the GMet dataset consisted of monthly climatological averages rather than a complete dated station time series, the comparison should be interpreted as town-level seasonal climatology agreement rather than full station-based temporal validation.

Table 7. CHIRPS–GMet town-level seasonal rainfall-climatology agreement metrics for Sunyani and Wenchi, 2000–2024.

Analysis	Paired observations	Pearson r	R^2	Regression slope	RMSE (mm)	MAE (mm)	Bias (mm)
Pooled Sunyani and Wenchi	24	0.983	0.966	0.917	14.80	11.16	-8.76
Sunyani	12	0.983	0.966	0.867	16.46	11.81	-10.40
Wenchi	12	0.986	0.972	0.958	12.93	10.51	-7.12

4.0 Discussion

4.1 Hydro-Climatic Variability and Temporal Trends

The results show that the Tano River Basin experienced substantial interannual hydro-climatic variability between 2000 and 2024, but no statistically significant monotonic trend was detected in annual rainfall, Rx1day, Rx5day, CDD, or LST. This indicates that annual conditions in the basin were dominated by year-to-year variability rather than by a persistent directional change over the 25-year study period. Similar rainfall behaviour has been reported across West Africa, where pronounced variability in annual rainfall and rainfall extremes can occur even when long-term rainfall trends remain weak or statistically non-significant (Nicholson, 2013; Sylla et al., 2016; Panthou et al., 2018).

The non-significant rainfall trend should not be interpreted as evidence of stable hydro-climatic conditions. Annual rainfall varied from 1144.48 mm in 2013 to 1766.45 mm in 2007, demonstrating large differences between relatively dry and wet years. The high rainfall recorded in 2007 occurred together with the highest Rx1day and Rx5day values, confirming that this year represented the strongest basin-average rainfall-extreme condition during the study period. In contrast, 2013 recorded the lowest annual rainfall, Rx1day, and Rx5day values, indicating a relatively weak annual rainfall regime.

The absence of significant trends in Rx1day and Rx5day also indicates that short-duration and multi-day rainfall extremes did not show a persistent increase or decrease over the study period. However, the large year-to-year variation remains hydrologically important because a single year with intense daily or multi-day rainfall can generate elevated runoff potential, particularly where drainage limitations, steep terrain, land-cover disturbance, or saturated soil conditions are present. Consequently, the analysis supports continued monitoring of rainfall extremes even in the absence of a significant long-term trend.

CDD showed a weak positive but non-significant slope. This result indicates that dry-spell duration varied among years but did not exhibit a statistically confirmed increase over time. The longest basin-average dry spell occurred in 2024, whereas the shortest was recorded in 2006. This pattern demonstrates that annual rainfall amount and dry-spell persistence do not necessarily follow the same temporal behaviour. A year may receive moderate rainfall but still experience long rain-free periods that affect soil moisture, agriculture, and water availability.

4.2 Vegetation Greenness and Land Surface Temperature

NDVI was the only variable that showed a statistically significant positive trend during the study period. The increase in basin-average NDVI indicates that vegetation greenness increased between 2000 and 2024. However, this finding should be interpreted carefully because NDVI trends can be influenced by several interacting factors, including rainfall timing, vegetation recovery, agricultural expansion, land-cover change, management practices, and annual image availability. Therefore, the observed increase in NDVI should be described as a statistically significant greening pattern rather than direct evidence of ecological resilience.

LST showed a positive Sen's slope, but the modified Mann–Kendall test indicated that the trend was not statistically significant. The results therefore do not provide sufficient evidence of a persistent basin-wide warming trend during the study period. Instead, LST was characterized by considerable interannual variability, with values ranging from 26.52°C to 32.07°C. Such variability may reflect differences in surface moisture, cloud cover, land-cover condition, atmospheric conditions, and annual compositing characteristics.

The weak and non-significant relationship between NDVI and LST further supports cautious interpretation. Although vegetation and land-surface temperature can be linked through evapotranspiration, shading, albedo, and surface-energy balance, the annual basin-average relationship in this study was weak. The results therefore do not support strong causal claims that vegetation greenness increased because of thermal adaptation or that LST directly controlled annual vegetation response. Similar caution has been emphasized in remote-sensing studies where NDVI and LST relationships vary according to season, vegetation type, soil moisture, and spatial scale.

4.3 Rainfall Extremes and Hydro-Climatic Relationships

The Spearman correlation results showed that annual rainfall was positively associated with Rx1day and Rx5day, while Rx1day and Rx5day were also positively related. These results indicate that wetter years generally coincided with stronger daily and five-day rainfall extremes. This pattern is expected because years with higher rainfall totals may contain more frequent or more intense rainfall events. Nevertheless, the correlations were moderate rather than perfect, indicating that total annual rainfall did not fully determine the magnitude of rainfall extremes.

The weak and non-significant association between rainfall and CDD indicates that annual rainfall total alone was insufficient to explain annual dry-spell persistence. This is an important finding because rainfall distribution and sequencing can be more relevant to agricultural water stress than annual rainfall amount. A year with moderate annual rainfall may still experience damaging dry spells if rainfall occurs in a few intense events separated by long dry periods.

The weak relationships involving NDVI, LST, rainfall, and CDD indicate that basin-average annual vegetation and thermal conditions were influenced by multiple factors beyond annual rainfall total. These may include soil moisture storage, land cover, agricultural activity, phenological timing, topography, and local atmospheric conditions. Therefore, the results should be interpreted as statistical associations rather than direct evidence of ecological mechanisms.

4.4 Interpretation of the Drought Condition Index and Extreme Rainfall Potential Index

A major contribution of the revised analysis is the separation of drought-related conditions from extreme-rainfall potential. The previous approach combined rainfall, rainfall extremes, dry spells, vegetation condition, and land-surface temperature into one integrated index. Although such an index may provide a general summary, it does not clearly distinguish whether high hydro-climatic stress is associated mainly with rainfall deficit, dry-spell persistence, vegetation deficit, thermal conditions, or high-intensity rainfall.

The entropy-weighted DCI and ERPI provide a more transparent interpretation of these contrasting processes. CDD received the highest entropy weight in the DCI, indicating that dry-spell persistence contributed the greatest information content to annual drought-condition variability. Rainfall deficit and NDVI deficit also contributed substantially, whereas LST had the lowest weight. This suggests that drought-related conditions in the basin were more strongly associated with rainfall sequencing and vegetation condition than with annual basin-average thermal variability.

For ERPI, Rx1day received the highest entropy weight, followed by annual rainfall and Rx5day. This indicates that short-duration rainfall intensity provided the greatest information contribution to annual extreme-rainfall potential. The prominence of Rx1day is consistent with the importance of intense rainfall events for runoff generation and localised flood potential in tropical

basins, where high-intensity rainfall can exceed infiltration capacity and rapidly concentrate over disturbed or impermeable surfaces.

The sensitivity analysis confirms that the revised indices were robust. The high rank correlations between entropy-weighted and equal-weight indices, together with the stability of results after $\pm 20\%$ weight perturbations, indicate that annual DCI and ERPI rankings were not strongly dependent on a single arbitrary weighting assumption. This strengthens confidence that the identification of high drought-condition years and high extreme-rainfall-potential years reflects the overall structure of the observed hydro-climatic data rather than a narrow weighting choice.

4.5 Annual Drought-Related and Extreme-Rainfall Conditions

The annual DCI and ERPI results reveal that drought-related conditions and extreme-rainfall potential did not peak in the same years. The highest DCI value occurred in 2024, followed by 2016, 2004, and 2013. These years combined relatively high rainfall deficit, longer dry spells, lower vegetation condition, and elevated thermal conditions. In particular, 2024 had the longest basin-average CDD value and the highest annual DCI, indicating that dry-spell persistence was important in shaping drought-related conditions.

The highest ERPI occurred in 2007, when annual rainfall, Rx1day, and Rx5day were all elevated. This result is consistent with the rainfall-extreme analysis, which identified 2007 as the year with the strongest daily and five-day rainfall events. High ERPI values were also observed in 2002, 2011, 2014, and 2023, indicating that extreme-rainfall potential occurred in several years even when annual rainfall totals were not necessarily at their maximum.

No year was classified as compound hydro-climatic stress at the annual basin-average scale. This indicates that basin-average drought-related and extreme-rainfall-related conditions did not simultaneously reach high levels during the same year. However, the absence of basin-average compound stress does not imply that localised compound conditions were absent. The spatial analysis demonstrated that drought-related and rainfall-extreme processes could overlap within limited parts of the basin.

4.6 Spatial Drought and Extreme-Rainfall Conditions

The spatial DCI maps showed a recurring pattern in which relatively high drought-related conditions occurred mainly in northern and central parts of the basin, whereas lower relative DCI values were often observed in southern grid cells. This pattern was particularly evident in 2013, 2016, and 2024. The spatial distribution suggests that rainfall deficit, dry-spell persistence, vegetation condition, and surface thermal characteristics varied substantially across the basin.

The ERPI maps showed a different spatial pattern. Relative extreme-rainfall potential was commonly concentrated in southern and central parts of the basin, particularly in 2007 and 2016. This contrast between relatively higher drought conditions in northern and central areas and relatively higher rainfall-extreme potential in southern and central areas indicates that hydro-climatic conditions were spatially heterogeneous. Such heterogeneity is consistent with the influence of regional rainfall gradients, moisture transport from the Gulf of Guinea, land-surface variability, and local environmental conditions in West African basins (Nicholson, 2013; Sylla et al., 2016).

The spatial hydro-climatic condition classes provided further evidence that drought-related and extreme-rainfall-related conditions could coexist within the same basin while affecting different locations. Compound stress was identified in 2000, 2007, and 2023, although it occupied only 4.27%, 8.24%, and 1.10% of the mapped basin area, respectively. The largest compound-stress extent occurred in 2007, which was also the year with the highest basin-average ERPI.

The limited extent of compound stress indicates that most grid cells were dominated either by drought-related conditions or by extreme-rainfall potential rather than by both simultaneously. This finding supports the need for geographically differentiated planning. Northern and central areas with relatively high drought-condition values may benefit from dry-spell preparedness, water conservation, soil-moisture management, and climate-smart agriculture. Southern and central areas with higher extreme-rainfall potential may require improved drainage, runoff-control measures, flood-warning systems, and land-use planning.

4.7 CHIRPS–IMERG Rainfall Agreement

The comparison between CHIRPS and GPM IMERG showed strong monthly basin-average agreement. The correlation coefficient of 0.939 and R^2 -value of 0.881 indicates that the two products captured similar temporal rainfall behaviour between 2001 and 2024. The regression slope of 1.030 indicates that CHIRPS reproduced the overall magnitude of rainfall variability reasonably well, while the positive bias of 6.66 mm indicates that CHIRPS was slightly higher than IMERG on average.

The RMSE of 27.96 mm and MAE of 18.56 mm indicate that differences between the products remained present at the monthly scale. These differences may reflect variation in satellite retrieval algorithms, spatial resolution, calibration procedures, and the representation of convective rainfall systems. Satellite rainfall products often show greater disagreement during high-intensity rainfall events because of difficulties in capturing localised convective storms and complex cloud structures (Dinku et al., 2018; Huffman et al., 2020).

The comparison should be interpreted as cross-product agreement rather than independent validation because both CHIRPS and IMERG are satellite-derived rainfall datasets. Nevertheless, the strong agreement provides confidence that CHIRPS captured the broad monthly rainfall variability

needed for basin-scale trend analysis, rainfall-extreme calculation, and hydro-climatic index development. Future work should incorporate quality-controlled rain-gauge and streamflow observations where available to provide a more independent assessment of rainfall performance and hydrological response.

4.8 Limitations and Future Research

Several limitations should be acknowledged. First, the analysis relied mainly on satellite-derived rainfall, vegetation, and land-surface-temperature products. These datasets provide consistent spatial coverage in data-scarce regions but do not replace ground-based rainfall, streamflow, soil-moisture, and vegetation observations. Uncertainty may arise from sensor characteristics, retrieval algorithms, cloud contamination, spatial resolution, and compositing procedures.

Second, the analysis was based on annual indicators. Annual aggregation is useful for identifying broad hydro-climatic variability, but it may conceal seasonal changes in rainfall onset, rainfall cessation, dry-spell timing, crop-water stress, and short-duration rainfall events. Future studies should examine monthly and seasonal hydro-climatic conditions, particularly during the major and minor rainy seasons.

Third, DCI and ERPI represent relative hydro-climatic conditions and rainfall-extreme potential rather than directly observed drought impacts or flood events. Actual drought and flood impact also depend on soil properties, topography, drainage capacity, river discharge, land cover, infrastructure, population exposure, and livelihood sensitivity. Future research should integrate streamflow, soil moisture, land-use change, flood inventories, crop information, and exposure data to develop more impact-oriented risk assessments.

Finally, spatial DCI and ERPI values were normalised independently within each selected year. Therefore, the maps show relative spatial drought and extreme-rainfall conditions within a year and should not be interpreted as direct absolute comparisons of index magnitude between different years. Despite this limitation, the approach provides a useful framework for identifying where drought-related and extreme-rainfall-related conditions were relatively concentrated within the basin during contrasting hydro-climatic years.

5.0 Conclusion

This study assessed hydro-climatic variability and spatial drought–extreme-rainfall conditions in the transboundary Tano River Basin between 2000 and 2024 using CHIRPS rainfall, Landsat-derived NDVI and LST, ETCCDI rainfall indices, entropy weighting, sensitivity analysis, and grid-based spatial mapping.

The results show that annual rainfall, Rx1day, Rx5day, CDD, and LST experienced substantial interannual variability but did not exhibit statistically significant monotonic trends over the study period. NDVI was the only variable with a significant positive trend, indicating an increase in basin-average vegetation greenness. Rainfall was significantly and positively associated with Rx1day and Rx5day, whereas most relationships involving CDD, NDVI, and LST were weak and non-significant.

The entropy-weighted framework successfully separated drought-related conditions from extreme-rainfall potential. CDD was the most influential component of the Drought Condition Index, while Rx1day was the most influential component of the Extreme Rainfall Potential Index. Sensitivity analysis demonstrated that annual index rankings remained stable under equal weighting and $\pm 20\%$ weight-perturbation scenarios, indicating that the results were not strongly dependent on the selected weighting scheme.

The strongest drought-related conditions occurred in 2024, 2016, 2004, and 2013, whereas the strongest extreme-rainfall potential occurred in 2007 and 2023. Although no year showed compound hydro-climatic stress at the annual basin-average scale, spatial analysis identified localised compound stress in 2000, 2007, and 2023. The largest compound-stress extent occurred in 2007, covering 8.24% of the mapped basin area.

Spatial analysis further showed that drought-related and extreme-rainfall-related conditions were not uniformly distributed across the basin. Relatively high drought conditions were commonly observed in northern and central areas, while relatively high extreme-rainfall potential was frequently concentrated in southern and central areas. These findings demonstrate that basin-wide averages alone can conceal important local contrasts in hydro-climatic conditions.

CHIRPS showed strong monthly agreement with GPM IMERG, supporting its use for basin-scale hydro-climatic analysis. However, the comparison represents cross-product agreement rather than independent validation. Future work should incorporate rainfall-gauge records, streamflow observations, soil moisture, land-use data, and observed flood and drought impacts to strengthen impact-based risk assessment.

Overall, the study provides a transparent and reproducible framework for distinguishing drought-related conditions from extreme-rainfall potential in tropical river basins. The findings can support spatially differentiated adaptation planning, including dry-spell preparedness, water-storage development, soil-moisture conservation, drainage improvement, flood-warning systems, and climate-resilient land-use management.

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736 **Conflicts of Interest**

737 The authors declare no conflict of interest.

738 **Ethics Approval**

739 Not applicable.

740 **Consent to Participate**

741 Not applicable.

742 **Consent for Publication**

743 Not applicable.

744 **Data Availability Statement**

745 All datasets used in this study are publicly accessible. CHIRPS daily precipitation data were obtained
746 from the Climate Hazards Centre. Landsat Collection 2 Level-2 surface reflectance and surface-
747 temperature imagery were obtained from the U.S. Geological Survey. GPM IMERG monthly
748 precipitation data were obtained from the National Aeronautics and Space Administration. Available
749 Ghana Meteorological Agency (GMet) rainfall observations for Sunyani and Wenchi were used for the
750 seasonal-climatology comparison. The Tano River Basin boundary was obtained from an available
751 basin-vector dataset.

752 Data processing and analysis were conducted using Google Earth Engine, Python, Google Colab, and
753 ArcGIS Pro. Processed annual hydro-climatic indicators, derived Drought Condition Index and Extreme
754 Rainfall Potential Index outputs, and analytical scripts are available from the corresponding author upon
755 reasonable request.

756 **CRedit Authorship Contribution Statement**

757 **George Owusu Amoah:** Conceptualisation, Methodology, Software, Formal analysis, Visualisation,
758 Data curation, Writing – original draft, Writing – review & editing.

759 **Rachel Olawoyin:** Conceptualisation, Supervision, Methodology, Writing – review & editing.

760 **Francis Quayson:** Methodology, Validation, Technical review, Writing – review & editing.

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764 Level-2 imagery, the National Aeronautics and Space Administration for GPM IMERG rainfall data,
765 and the Ghana Meteorological Agency for the available station rainfall data used in the seasonal-

climatology comparison. The authors also acknowledge Google Earth Engine for providing cloud-based geospatial data-processing infrastructure.

Code and Software Availability

The analytical workflow was implemented using Google Earth Engine, Python, Google Colab, and ArcGIS Pro. Custom scripts used to derive annual rainfall, maximum 1-day rainfall, maximum 5-day rainfall, consecutive dry days, NDVI, land surface temperature, entropy-weighted Drought Condition Index, and Extreme Rainfall Potential Index are available from the corresponding author upon reasonable request.

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