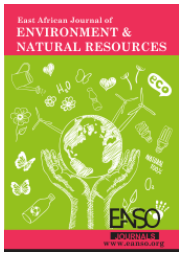
Article DOI: https://doi.org/10.37284/eajenr.9.3.5790



East African Journal of Environment and Natural Resources
eajenr.eanso.org
Volume 9, Issue 3, 2026
Print ISSN: 2707-4234 | Online ISSN: 2707-4242
Title DOI: https://doi.org/10.37284/2707-4242

EAST AFRICAN NATURE & SCIENCE ORGANIZATION

Original Article

Long-Term Drought Variability in Southwestern Uganda: A Comparative Analysis of Ground and Satellite Rainfall Data for Mbarara

Tom Mutabazi[1], Upton Nuwagira[1], Valence Habyarimana[1], David Mubiru[1], Priscilla Muheki[1], Jackline Kampire[1], Yonah Ntegyerize[1] & Emmanuel Munyarugero[1]*

[1] Mbarara University of Science and Technology, P. O. Box 1410, Mbarara, Uganda.
[*] Author for Correspondence ORCID ID; https://orcid.org/0000-0002-9949-0403; Email: tmutabazi@must.ac.ug

Article DOI: https://doi.org/10.37284/eajenr.9.3.5790

Date Published: *15 September 2026*

Keywords: *Climate change, Seasonal rainfall trends, SPI Drought analysis.*

ABSTRACT

This study analysed drought occurrence in Mbarara District using ground-based observations and satellite-derived rainfall estimates from the Climate Hazards Infrared Precipitation with Stations (CHIRPS) data (for the period 1981–2024) and the Climate Prediction Center Morphing Technique (CMORPH) datasets (1998–2023). A comparison between satellite-derived and in-situ rainfall data was performed using simple linear regression and error metrics, while seasonal trends were assessed using the non-parametric Mann-Kendall and Theil-Sen methods. Results show that CHIRPS strongly agrees with ground-based observations (R2 ~ 0.93, RMSE ≈ 32.6 mm, PBIAS = 6.5%), while CMORPH exhibited weaker agreement (R2 ~ 0.47, RMSE ≈ 42.9 mm, PBIAS = −17.0%). Drought characterisation using the Standardised Precipitation Index (SPI) reveals distinct drought episodes experienced during 1984–1993, 1999–2004, 2009–2013, 2017, and 2022–2024. Analysis of seasonal rainfall variability shows a non-significant decrease in rainfall during the September-October-November (SON) season. This study provides one of the longest station-satellite-validated drought analyses for southwestern Uganda using CHIRPS data. The observed patterns and episodic drought events highlight a need to strengthen adaptive strategies in agriculture and water resource management to mitigate the socioeconomic impacts of drought in the region.

APA CITATION

Mutabazi, T., Nuwagira, U., Habyarimana, V., Mubiru, D., Muheki, P., Kampire, J., Ntegyerize, Y., & Munyarugero, E. (2026). Long-Term Drought Variability in Southwestern Uganda: A Comparative Analysis of Ground and Satellite Rainfall Data for Mbarara. *East African Journal of Environment and Natural Resources*, *9*(3), 734-751. https://doi.org/10.37284/eajenr.9.3.5790.

CHICAGO CITATION

Mutabazi, Tom, Upton Nuwagira, Valence Habyarimana, David Mubiru, Priscilla Muheki, Jackline Kampire, Yonah Ntegyerize and Emmanuel Munyarugero. (2026). "Long-Term Drought Variability in Southwestern Uganda: A Comparative Analysis of Ground and Satellite Rainfall Data for Mbarara", *East African Journal of Environment and Natural Resources* 9 (3), 734-751. https://doi.org/10.37284/eajenr.9.3.5790.

HARVARD CITATION

Mutabazi, T., Nuwagira, U., Habyarimana, V., Mubiru, D., Muheki, P., Kampire, J., Ntegyerize, Y., & Munyarugero, E. (2026). "Long-Term Drought Variability in Southwestern Uganda: A Comparative Analysis of Ground and Satellite Rainfall Data for Mbarara", *East African Journal of Environment and Natural Resources*, 9 (3), pp. 734-751. doi: 10.37284/eajenr.9.3.5790.

 This work is licensed under a Creative Commons Attribution 4.0 International License

Article DOI: https://doi.org/10.37284/eajenr.9.3.5790

IEEE CITATION

T., Mutabazi, U., Nuwagira, V., Habyarimana, D., Mubiru, P., Muheki, J., Kampire, Y., Ntegyerize & E., Munyarugero, "Long-Term Drought Variability in Southwestern Uganda: A Comparative Analysis of Ground and Satellite Rainfall Data for Mbarara", *EAJENR*, vol. 9, no. 3, pp. 734-751, Sep. 2026.

MLA CITATION

Mutabazi, Tom, Upton Nuwagira, Valence Habyarimana, David Mubiru, Priscilla Muheki, Jackline Kampire, Yonah Ntegyerize & Emmanuel Munyarugero. "Long-Term Drought Variability in Southwestern Uganda: A Comparative Analysis of Ground and Satellite Rainfall Data for Mbarara", *East African Journal of Environment and Natural Resources*, Vol. 9, no. 3, Sep. 2026, pp. 734-751, doi:10.37284/eajenr.9.3.5790.

INTRODUCTION

Global greenhouse gas (GHG) emissions from human and natural sources continue to rise, leading to a steady increase in global temperatures referred to as global warming (Arrhenius, 1897; Ripple et al., 2024; Jackson et al., 2024). These emissions have been attributed mainly to man-made activities (e.g., urbanisation, deforestation, poor management of industrial and agricultural waste, fossil fuel use) rather than natural (e.g., volcanic eruptions, wildfires) causes (Ripple et al., 2023; Samal et al., 2024). According to the IPCC Sixth Assessment Synthesis Report (Masson-Delmotte et al., 2023), the global mean surface temperature rose by about 1.1^0C above pre-industrial levels (1850–1900) during 2011–2020. This warming, which is largely attributed to accelerated urbanisation and industrial development globally (Lee et al., 2023; Forster, 2025), has led to numerous environmental impacts such as severe heatwaves, prolonged droughts, intense rainfall, landslides, and flash floods (van der Wiel & Bintanja, 2021; Vautard et al., 2023). These climate change disasters threaten agricultural productivity and food security (van Asten et al., 2011; Twongyirwe et al., 2019; Bwambale & Mourad, 2022; Nansamba et al., 2022), income (Bhaga et al., 2020), and human health (Epstein et al., 2020; Wang et al., 2023; Maslin et al., 2025; Ssentongo et al., 2025).

Various studies have been conducted to validate rainfall data products estimated from satellite-based precipitation measurements (e.g., Dinku et al., 2007; Kimani et al., 2017; Dinku et al., 2018; Aksu & Akgül, 2020; Omay et al., 2025). Omay et al. (2025) assessed the accuracy of satellite-based rainfall products over East Africa and the IGAD member states for the period 2001–2020. Out of the nine gridded satellite-based rainfall estimates that they considered, the Climate Prediction Center (CPC) MORPHing technique (CMORPH, Joyce et al., 2004; Xie et al., 2017) emerged as the best in terms of performance, while the Climate Hazards Infrared Precipitation with Stations (CHIRPS v2, Funk et al., 2015, hereafter referred to as CHIRPS) ranked the second best. This is supported by other previous works carried out over East Africa (e.g., Kimani et al., 2017), where CMORPH demonstrated the highest accuracy relative to in situ rain gauge data. However, the accuracy of satellite-derived rainfall data products varies across locations due to factors such as topography, rainfall intensity, and the availability of long-term high-quality ground-based gauge data (Kaprom et al., 2025; Akinsanola et al., 2026). Some reports suggest that CHIRPS performs better over equatorial East Africa (e.g., Ageet et al., 2022). A comparative assessment between ground-based in situ rainfall observations and satellite-derived precipitation products was therefore performed in order to evaluate their consistency and reliability for rainfall and drought analysis in Mbarara.

Problem Statement

Drought is one of the major climate-related hazards affecting agriculture, water availability, and livelihoods in Uganda. In Mbarara and the surrounding cattle corridor, variability in rainfall together with increasing temperature extremes may increase vulnerability to drought and water stress. The vulnerability of agriculture to drought is further demonstrated by van Asten et al. (2011), who reported substantial reductions in Uganda's highland banana production during dry periods. Owoyesigire et al. (2016) reported significant increases in hot days and warm nights in Mbarara, with potential implications for heat stress, surface-water availability, and pasture conditions.

 This work is licensed under a Creative Commons Attribution 4.0 International License

Article DOI: https://doi.org/10.37284/eajenr.9.3.5790

Despite these concerns, drought conditions in Mbarara have not been sufficiently characterised. Previous studies have mainly examined rainfall and temperature variability, agricultural impacts, or drought at regional and national scales (Kyatengerwa et al., 2020; Byakatonda et al., 2021; Okirya & Du Plessis, 2024; Ssembajwe et al., 2025). Consequently, there is limited information on the frequency, duration, severity, and persistence of drought in Mbarara across different timescales. In addition, reliance on individual meteorological stations can limit the availability and spatial representation of long-term rainfall observations, while annual rainfall totals may not adequately capture seasonal and short-term rainfall deficits that contribute to drought. Satellite-derived rainfall products provide an opportunity to address some of these limitations by offering continuous and spatially extensive rainfall estimates. However, their reliability varies by region (Okirya & Du Plessis, 2024; Omay et al., 2025) and therefore requires assessment against ground-based observations before they are used for local drought monitoring. There is consequently a need to evaluate the performance of satellite-derived rainfall products and use reliable rainfall estimates to characterise drought conditions in Mbarara.

This study therefore compares long-term drought variability derived from ground-based gauge data and satellite-derived rainfall data products for Mbarara, providing evidence on their consistency and suitability for drought assessment in southwestern Uganda. The study utilized Standardized Precipitation Index (SPI; McKee et al., 1993) in the analysis and assessment of drought using in situ and satellite data products. SPI values were compared to determine whether differences in ground-based and satellite rainfall data lead to different estimates of long-term drought characteristics in Mbarara. Unlike the Standardised Precipitation Evapotranspiration Index (SPEI), which incorporates both precipitation and potential evapotranspiration (Vicente-Serrano et al., 2010; Beguería et al., 2014), SPI depends solely on precipitation. However, both SPI and SPEI have proved reliable for drought analysis (Gumus, 2023; Filipović et al., 2025; Mungul et al., 2025; Mukama et al., 2025). The primary aim of this study is twofold: (i) to evaluate the feasibility of using satellite-derived precipitation products for drought monitoring and analysis, and (ii) to assess the historical occurrence and characteristics of droughts in Mbarara for the period 1981–2024.

DATA AND METHODS

Study Area and Data

Mbarara District and surrounding areas (southwestern region) generally experience a bimodal rainfall pattern, with two main rainy seasons: March-April-May (MAM) and September-October-November (SON). December-January-February (DJF) and June-July-August (JJA) are usually dry in most parts of the country (Nicholson, 2017). The rain gauge data used in this study are for the Mbarara Kakoba meteorological station located at a latitude of 0° 37′00.05″ S and longitude $\approx 30^\circ$ 39′00.04″ E. The elevation of this site is ~1412 m above sea level. The study used gauge data from the Mbarara Kakoba station. Monthly rainfall data covering the period 1980–2024 were obtained from the records of the Uganda National Meteorological Authority (UNMA) and made available by a co-author.

CHIRPS data which is publicly available at https://data.chc.ucsb.edu/products/CHIRPS-2.0/ is a high-resolution $0.05^\circ \times 0.05^\circ$ (~5 km × 5 km) global precipitation dataset developed by the Climate Hazards Group at the University of California, Santa Barbara, with rainfall estimates on daily, pentad (5-day), decad (10-day), monthly, and annual timescales spanning long periods of time, from 1981 to the near-present (Funk et al., 2015). Monthly rainfall data for the period 1981 to 2024 were downloaded. The CMORPH data products are also publicly available at https://www.ncei.noaa.gov/data/, from which CMORPH monthly rainfall data for the period 1998–2023 were obtained.

 This work is licensed under a Creative Commons Attribution 4.0 International License

Article DOI: https://doi.org/10.37284/eajenr.9.3.5790

Methods

The CMORPH and CHIRPS data were analysed using various Python packages. These include 1) Xarray (Hoyer & Hamman, 2017) for multi-dimensional array handling of gridded data, making it easy to manage time-series satellite data, 2) netCDF4 (Whitaker et al., 2024) and Pandas (McKinney et al., 2011) for NetCDF format and data manipulation (data merging, grouping, rolling computations, and time indexing). Other packages used include Geospatial Data Abstraction Library (Gdal & Warmerdam, 2008) via Osgeo (McInerney et al., 2015; Rouault et al., 2026). The Osgeo package provides Python bindings for GDAL. These help access raster metadata, crop to a specified region or bounding box, as well as extract pixel values for analysis.

For CHIRPS, global monthly rainfall datasets were used. The monthly precipitation values for Mbarara were assumed to be those corresponding to the coordinates of the Mbarara-Kakoba meteorological station, and the values were extracted from the clipped NetCDF files using Xarray by selecting the grid cell closest to the station's geographic coordinates (using the data variable "precip"). For CMORPH, daily rainfall data products were used. They were subsequently combined by coordinates and resampled into total monthly rainfall datasets. The variable "cmorph" was used to obtain the rainfall values corresponding to the grid nearest to the area of interest (coordinates corresponding to Mbarara Kakoba station). The extracted rainfall values were organised into clean, structured formats (with time as the index) for easy analysis and visualisation. A linear least-squares regression was performed to compare satellite-derived precipitation data (CHIRPS and CMORPH) with in situ ground-based gauge measurements. The degree of agreement was assessed using the coefficient of determination (R^2) and the RMSE calculated using Eqn. (1):

$$RMSE = \sqrt{\frac{1}{n}\sum_{i=1}^{n}\left(P_i - \hat{P}_i\right)^2}, \quad \ldots\ldots (1)$$

Where P_i is the actual observed ground-based precipitation value, $\hat{P}_i$ is the estimated or satellite-derived value, and n is the number of observations. In addition, the percent bias (PBIAS) was determined using Eqn. (2);

$$PBIAS = \frac{\sum_{i=1}^{n}(S_i - O_i)}{\sum_{i=1}^{n} O_i} x100, \quad \ldots\ldots (2)$$

Where S_i is the satellite-derived rainfall value corresponding to the observed (gauge) value, O_i, and n is the number of observations.

The SPI corresponding to a time scale, t in months, can be calculated as a deviation from the mean after normalising it by the standard deviation over the entire period of study, T, using Eqn. (3) (e.g., McKee et al., 1993, 1995):

$$SPI = \frac{P - \bar{P}}{\sigma} \quad \ldots\ldots (3)$$

Where P is the precipitation for time scale t, $\bar{P}$ is the mean precipitation over a long period T, while σ is the standard deviation associated with the long-period precipitation. The time series rainfall records from the Mbarara-Kakoba meteorological weather station and CHIRPS precipitation data were treated separately. The time series rainfall data were aggregated to the specified timescale (e.g, 3 months) and subsequently fitted to a gamma probability distribution function (Stagge et al., 2015) using Eqn. (4)

$$f(x) = \frac{x^{\alpha-1}}{\beta^{\alpha}\Gamma(\alpha)} exp\left(\frac{-x}{\beta}\right) for x > 0, \quad \ldots\ldots (4)$$

Where α and β are the shape and scale parameters, respectively. A gamma probability distribution function is widely recognised as the optimal distribution for modelling precipitation data and for computing SPI (McKee et al., 1993; Guttman,

 This work is licensed under a Creative Commons Attribution 4.0 International License

Article DOI: https://doi.org/10.37284/eajenr.9.3.5790

1999). The cumulative density function (CDF) was thereafter computed using Eqn. (5):

$$F(x) = \frac{1}{\beta^{\alpha}\Gamma(\alpha)} \int_0^x x^{\alpha-1} \, exp\left(\frac{-x}{\beta}\right) dx, \quad \ldots\ldots (5)$$

Where $\Gamma(\alpha)$ is the gamma function defined as:

$$\Gamma(\alpha) = \int_0^{\infty} x^{\alpha-1} \, exp(-x) dx.$$

The CDF was normalised so as to transform it into standard normal variables known as SPI by following the approximation technique developed by Abramowitz and Stegun (1965). These steps were carried out within the SciPy package (Virtanen et al., 2020; Gommers et al., 2024). The maximum likelihood estimate (MLE method) approximates the scale and shape parameters as follows:

$$\alpha = \frac{1}{4A}\sqrt{1 + \frac{4A}{3}} \text{and} \beta = \frac{\bar{x}}{\alpha},$$

Where A represents the sample statistic for n observations with an average value, $\bar{x}$, expressed as:

$$A = ln(\bar{x}) - \frac{\sum ln\,(x)}{n}.$$

Different time scales (1, 2, 3, 4, 6, 12, 24, and 48 months) were used to compute SPI, capturing various classes of drought from short-term meteorological and agricultural drought to long-term water scarcity and hydrological drought. The obtained SPI threshold values were used to classify drought according to McKee et al. (1993). Table 1 shows drought classification based on SPI values and the corresponding event probabilities as suggested by McKee et al. (1993). The classification of periods as wet or dry was guided by the obtained SPI values, which were compared against the threshold values presented in Table 1. Drought classification was performed independently for CHIRPS and ground-based data, after which the outcomes were compared to assess consistency.

Table 1: SPI Values and Corresponding Event Probabilities

SPI value	Category	Probability (%)
2.00 or more	Extremely wet	2.3
1.50 to 1.99	Severely wet	4.4
1.00 to 1.49	Moderately wet	9.2
0 to 0.99	Mildly wet	34.1
0 to −0.99	Mild drought	34.1
−1.00 to −1.49	Moderate drought	9.2
−1.50 to −1.99	Severe drought	4.4
−2 or less	Extreme drought	2.3

Source: *(McKee et al., 1993)*

Trend analysis was performed using the non-parametric Mann-Kendall (MK) test (Mann, 1945; Kendall, 1948) and Theil-Sen's method (Theil, 1950; Sen, 1968). Severe drought conditions are mostly experienced during the JJA season, while moderate droughts tend to occur during the DJF period (Palmer et al., 2023). The highest drought risks are those experienced during the crop growing season, especially MAM, as these droughts often result in crop failure and pasture loss (Byakatonda et al., 2021; Ngoma et al., 2021; Ojara et al., 2024a). The wettest conditions and most beneficial to crop growing, typically occur during the MAM season, which is the longest rainy period, followed by moderately wet conditions during SON (Nsubuga & Rautenbach, 2018; Omay et al., 2023). Seasonal trends were therefore determined for each of these four periods: MAM, JJA, SON, and DJF, to assess temporal variations of drought.

RESULTS AND DISCUSSION

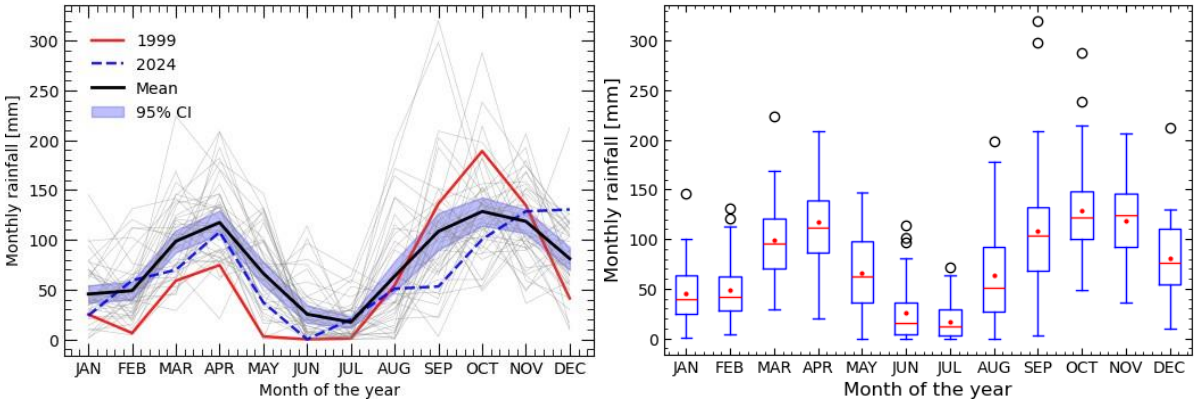
Figure 1 shows the distribution of monthly rainfall for ground-based data over a period of 45 years (1980–2024) with emphasis on a few selected years: 1999 (long and extreme drought

This work is licensed under a Creative Commons Attribution 4.0 International License

Article DOI: https://doi.org/10.37284/eajenr.9.3.5790

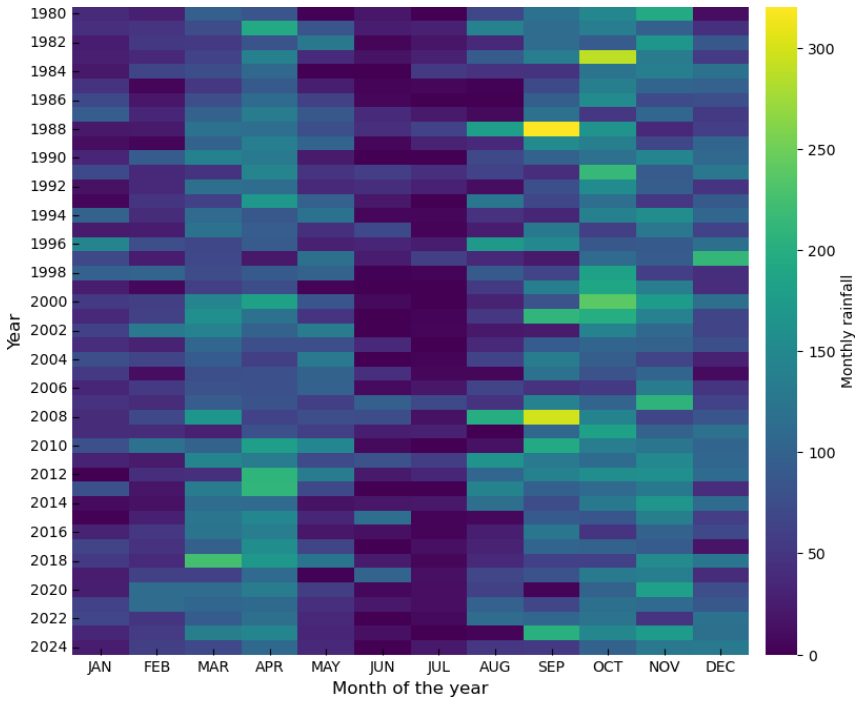
conditions), and 2024 (mild drought). The two main rainy seasons (MAM and SON), as well as the dry spell (JJA and DJF), are clearly distinguishable from the displayed data. The bottom panel of Fig. 1 presents a 2-D heatmap illustrating the detailed biannual rainfall distribution, with the colour scale representing rainfall intensity. Historically, Mbarara receives its peak rainfall during the MAM and SON seasons (Nsubuga et al., 2014; Okirya & Du Plessis, 2024), providing critical moisture necessary for agricultural activities and crop growth. In contrast, DJF and JJA seasons are generally dry across the region. Various online sources (e.g., Tenywa, 2007; Arinaitwe, 2024) reported dry and drought events across the period of study: 1998–1999, 2005, 2008, 2010–2011, 2014–2019, 2020–2022, 2023, and 2024. These are clearly visible in the heatmap presented in Fig. 1. It should be noted that the longest dry periods were observed between 1998 and 2002, characterized by monthly rainfall totals of less than 8 mm, as can be seen in the heatmap shown in Fig. 1. Considering the amount of rainfall recorded, the most prolonged dry period happened in 1999, when rainfall for May, June, and July fell below 3 mm per month (on average) as can be seen in the top left-hand panel of Fig. 1. Such early onset of dry spell which happened during crop growing season is disastrous and indeed led to severe reductions in crop yields, particularly in maize, beans, and banana plantations (Anyamba et al., 2002). The light-blue shaded region in the top left-hand panel shows the 95% confidence level around the average rainfall (shown in black) over the study period. The top right-hand panel presents a box-and-whisker plot of the same rainfall distribution over the 45-year period. The box represents the interquartile range (IQR), encompassing the middle 50% of the data, with the lower and upper bounds corresponding to the 25th and 75th percentiles, respectively. The horizontal red line within the box indicates the median, while the red filled circles represent average rainfall for each month during the study period. The whiskers extend to the data range within 1.5 times the IQR. Data points beyond this range are represented by black open circles.

Figure 1: Distribution of Annual Monthly Rainfall for Ground-Based Rain Gauge Data for the Period 1980–2024



 This work is licensed under a Creative Commons Attribution 4.0 International License

Article DOI: https://doi.org/10.37284/eajenr.9.3.5790

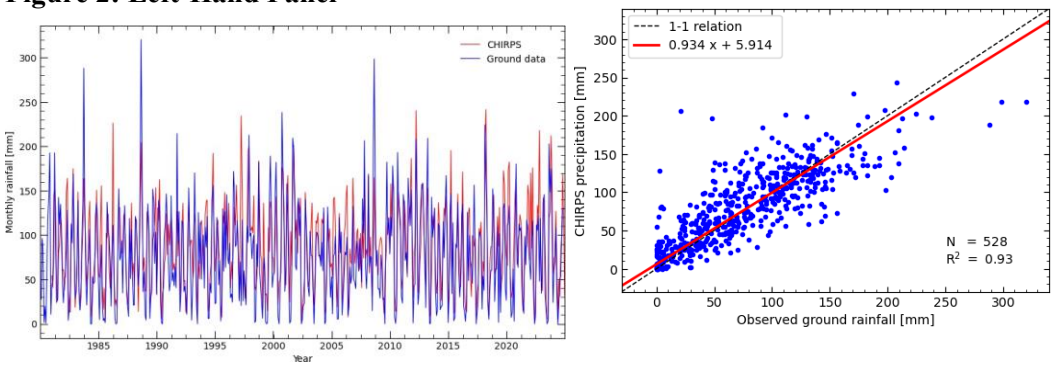


Left-hand panel: Annual monthly rainfall distribution showing average rainfall (black solid line) and the 95% confidence interval (light blue shaded region). Right-hand panel: A box-and-whisker plot showing the mean rainfall (red filled circles), median (horizontal red solid lines), and interquartile range over the study period. Bottom panel: Bimodal rainfall distribution using a two-dimensional heat map.

Comparison of in situ and Satellite-Derived Rainfall Data

Based on simple regression analysis, CHIRPS showed a strong linear relationship with ground-based gauge measurements ($R^2 \sim 0.93$), while CMORPH exhibited a weaker correlation ($R^2 \sim 0.47$) and greater scatter. While both showed high correlation coefficient (Pearson $r = 0.81$ for CHIRPS and $r = 0.73$ for CMORPH data), percent biases of 6.5% with CHIRPS and −17.0% for CMORPH were observed relative to the gauge data. Consequently, CMORPH data were excluded from further analysis. Figure 2 shows a comparison of ground-based and CHIRPS monthly rainfall data. The left-hand panel compares the distributions, with ground-based observations shown in blue and CHIRPS estimates in red. The right-hand panel illustrates the strong correlation between the two datasets. In the right-hand panel, the black dashed line indicates the one-to-one relationship, and the red solid line represents the linear least-squares fit. The two datasets exhibit excellent agreement.

Figure 2: Left-Hand Panel



 This work is licensed under a Creative Commons Attribution 4.0 International License

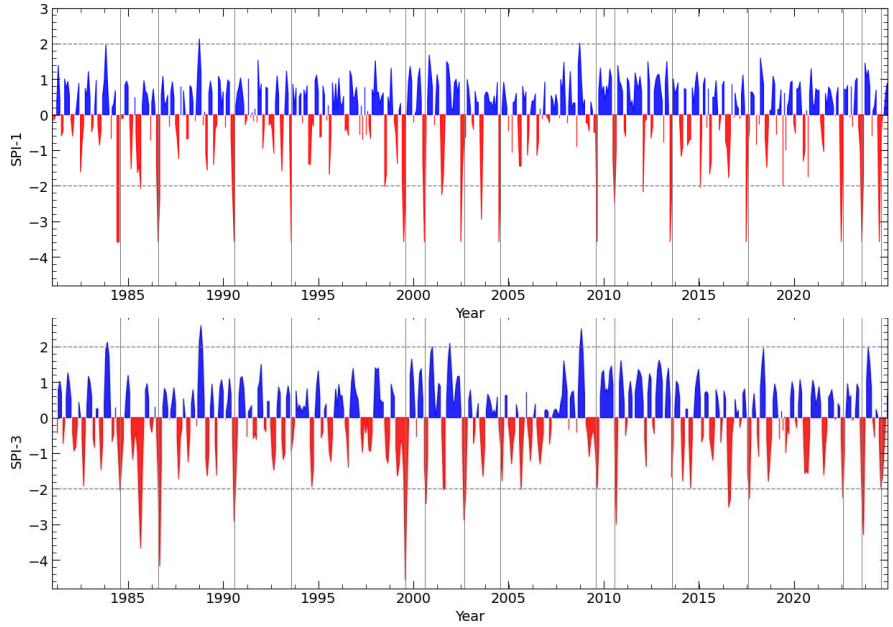
Article DOI: https://doi.org/10.37284/eajenr.9.3.5790

Distribution of ground-based rain gauge data (blue) and CHIRPS data (red). Right-hand panel: Relation between ground-based and CHIRPS data. The black dashed line shows a one-to-one relation, while the red solid line represents a linear fit to the data.

SPI

Figure 3 shows drought conditions on a scale of 1 month (top panel) and 3 months (bottom panel) – see also Fig. 4 for scales of 2, 4, 6, 12, 24, and 48 months. On a scale of one month, severe droughts (SPI < −1.5) lasting for at least two months (and a severity value greater than 5) exist for the years 1984, 1986, 1990, 1999, 2002, 2004, 2013, and 2023. These happened mainly between the months of June and August. Figure 4 shows wet and drought conditions using SPI computed using in situ and CHIRPS data. There is good agreement between the model and observed in situ data, with a correlation coefficient greater than 0.6 for scales of 2, 3, 4, and 6 months. The correlation becomes weaker at larger scales (12, 24, and 48 months), as shown in Figure 5, probably due to data paucity – data smoothing may amplify short-term variability and small systematic differences between the two datasets.

Figure 3: Occurrence of Drought at a Scale of One (top panel) and Three Months (bottom panel) Based on Ground Gauge Data

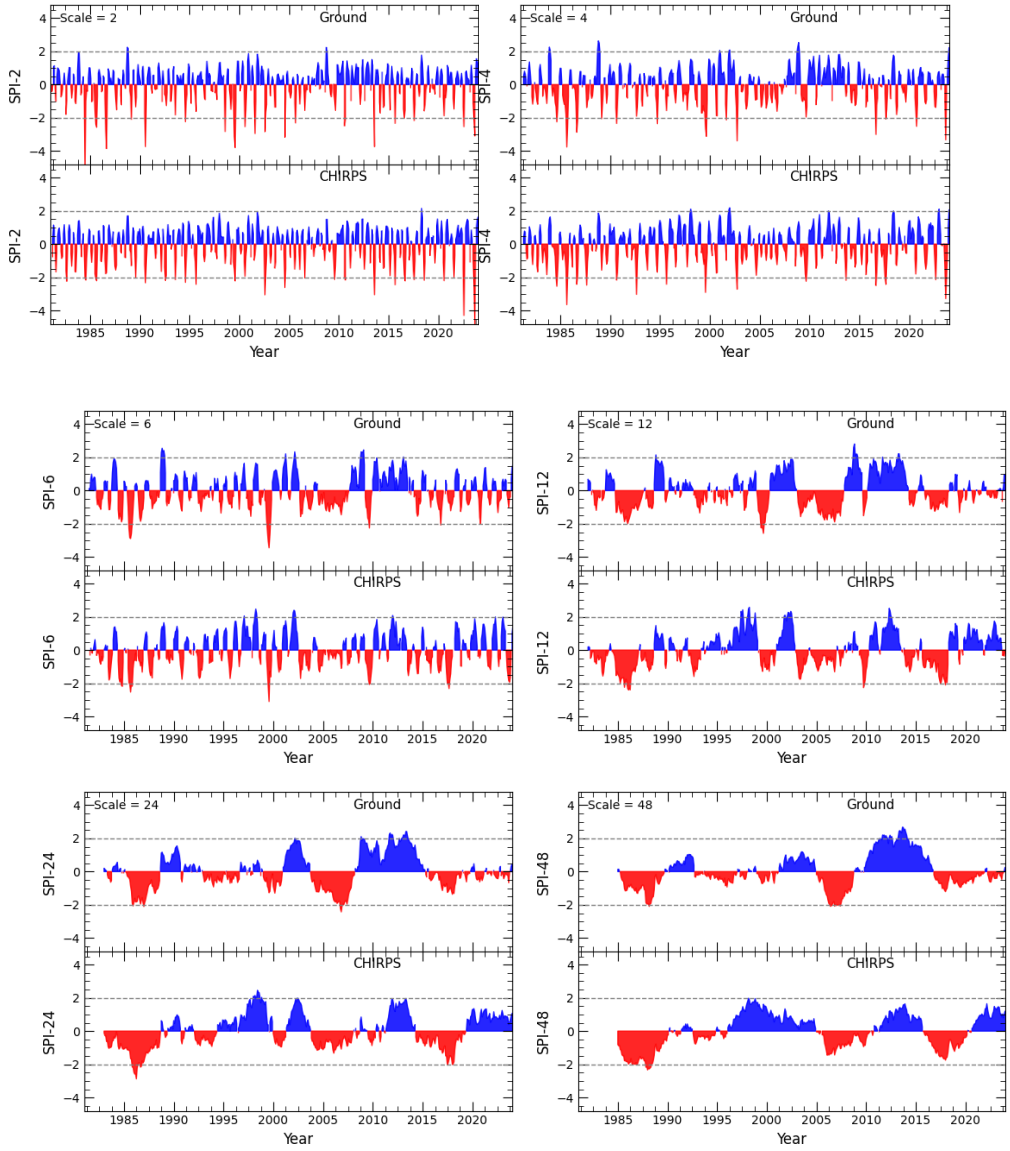


The vertical gray lines show extreme drought during the period 1984–1993, 1999–2004, 2009–2013, 2022–2024, as well as the drought experienced in 2017. These coincide with reported droughts in Mbarara district and surrounding areas.

 This work is licensed under a Creative Commons Attribution 4.0 International License

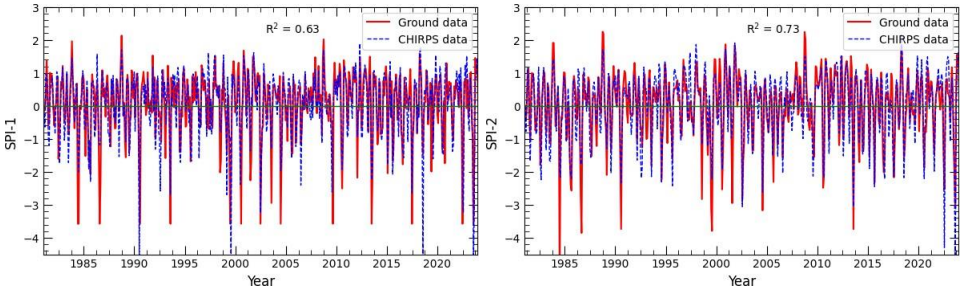
Article DOI: https://doi.org/10.37284/eajenr.9.3.5790

Figure 4: Standardised Precipitation Indices Measured Using a Ground-Based Rain Gauge and CHIRPS Data.



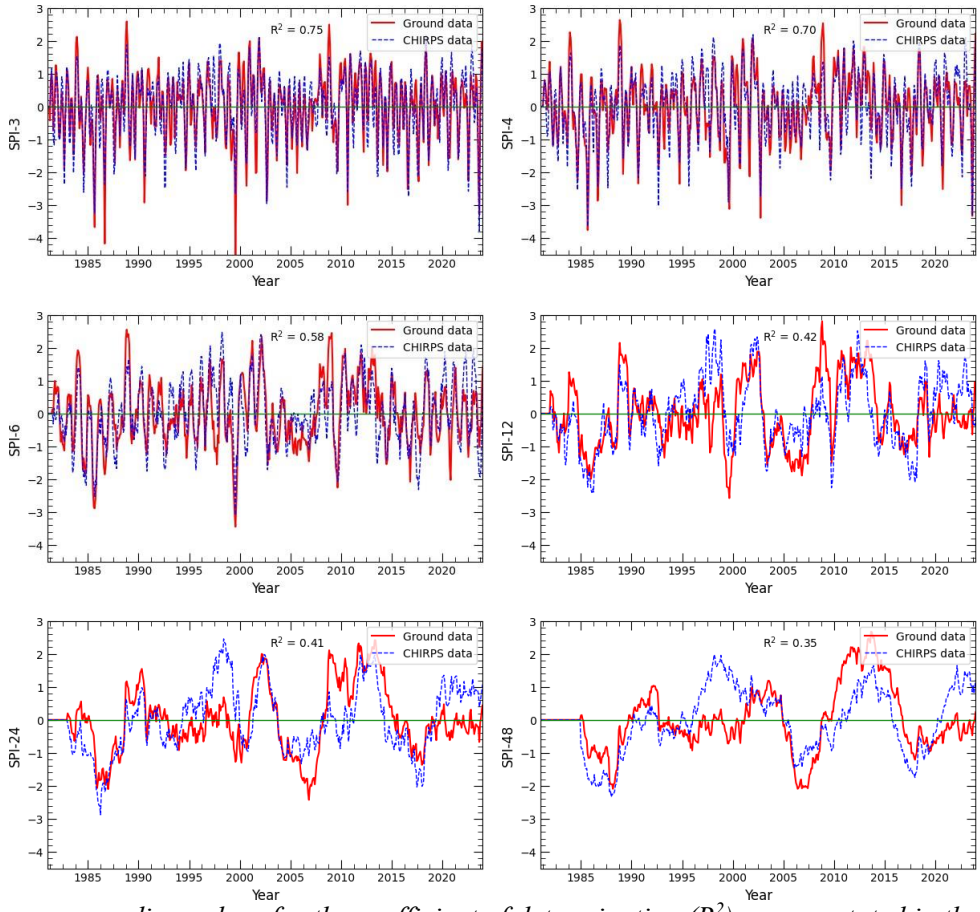
The wet and dry periods are represented by the blue and red colours, respectively.

Figure 5: Comparison of SPI values from CHIRPS (blue dashed line) and ground-based rain gauge (red solid line) data over different timescales



 This work is licensed under a Creative Commons Attribution 4.0 International License

Article DOI: https://doi.org/10.37284/eajenr.9.3.5790



The corresponding values for the coefficient of determination (R^2) are annotated in the figure.

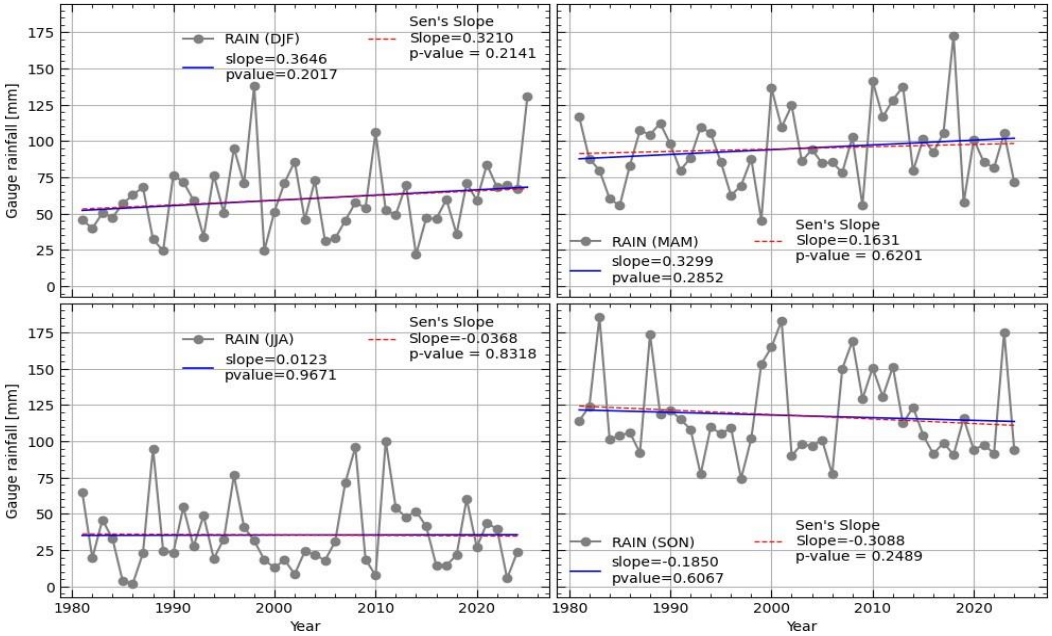
Trend Analysis

To assess variations in rainfall, the non-parametric Mann-Kendall (MK) test (Mann, 1945; Kendall, 1948) and Theil-Sen's method (Theil, 1950; Sen, 1968) were used. The MK test indicates whether a trend exists without assuming any specific data distribution. This makes it suitable for analysing trends in climate data. Sen's slope estimator was used to quantify how strong the trend is. The seasonal analysis of drought variability in Mbarara shows that the most severe drought events predominantly occurred during the JJA season, whereas moderate drought conditions were more frequently observed during DJF. This seasonal pattern is consistent with the climatological characteristics of rainfall in Mbarara and agrees with previous observations of seasonal drought variability in Uganda (Nicholson, 2017; Ojara et al., 2024b). To capture these intra-annual variations, trend analyses were conducted separately for MAM, JJA, SON, and DJF. As shown in Fig. 6, rainfall in Mbarara exhibited an increasing trend during DJF (S = 3.8 mm year^{-1}) and a decreasing trend during SON (S = − 3.7 mm year^{-1}). However, neither trend was statistically significant ($p > 0.05$), indicating that the observed seasonal changes do not provide sufficient evidence of a systematic long-term change in rainfall. These findings contrast with those of Owoyesigire et al. (2016), who reported a significant warming trend in Mbarara during 1961–2013, with potential implications for heat stress and surface-water availability.

 This work is licensed under a Creative Commons Attribution 4.0 International License

Article DOI: https://doi.org/10.37284/eajenr.9.3.5790

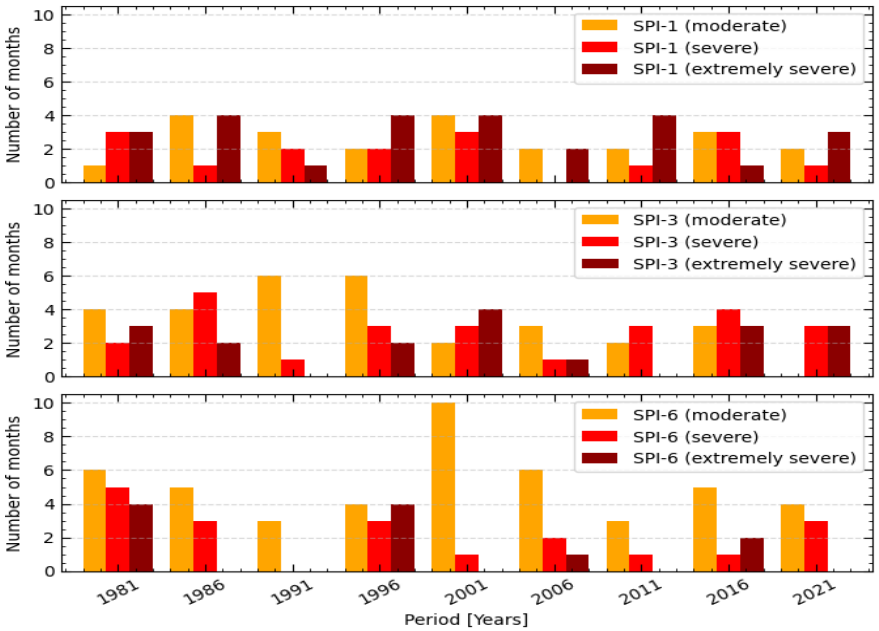
Figure 6: Seasonal Variability of Rainfall



The analysis indicates positive rainfall trends during DJF, MAM, and JJA seasons. The SON season exhibits a negative trend, suggesting a decline in rainfall during this period.

To assess severity, drought was further classified into three severity categories based on SPI thresholds: (i) $-1.0 \leq SPI < -1.5$ (moderate drought), (ii) $-1.5 \leq SPI < -2$ (severe drought), and (iii) $SPI \leq -2$ (extreme drought). The data were then aggregated into consecutive five-year periods, and for each period, the number of months falling within each drought category (i.e., drought frequency) was determined. The findings (presented in Fig. 7) indicate that at least one episode of severe or extreme drought occurred in every five-year period analysed.

Figure 7: Temporal Distribution of Drought Frequency across Five-Year Periods based on SPI Thresholds



 This work is licensed under a Creative Commons Attribution 4.0 International License

Article DOI: https://doi.org/10.37284/eajenr.9.3.5790

Drought conditions were classified as moderate ($-1.0 \leq SPI < -1.5$), severe ($-1.5 \leq SPI < -2$), and extreme ($SPI \leq -2$). Each bar represents the number of months within each drought category for the corresponding five-year interval.

Limitations of the Study

The validation of satellite and gauge data was limited to a point-to-pixel comparison using a single meteorological station. This may not fully represent regional rainfall variability. In addition, the drought analysis relied mainly on SPI, which considers only precipitation and excludes temperature and evapotranspiration effects. Nonetheless, the strong agreement between CHIRPS and station observations demonstrates the usefulness of satellite-derived rainfall products for drought monitoring in data-scarce regions, as they provide important baseline information for climate risk assessment, drought early warning, agricultural planning, and water resource management.

CONCLUSION

While East Africa generally receives bimodal rainfall (Dinku et al., 2007; Nicholson, 2017; Ngoma et al., 2021), it also experiences very strong spatial rainfall and climate variability (Liebmann et al., 2014; Nicholson, 2015) due to complex topography (Palmer et al., 2023). This study assessed rainfall variability, satellite rainfall performance, and historical drought occurrence in Mbarara, southwestern Uganda, using ground-based observations and satellite-derived rainfall estimates. The validation analysis showed that CHIRPS performed substantially better than CMORPH in reproducing gauge observations, with $R^2 \approx 0.93$ and 0.47, respectively. Drought characterisation was therefore based on gauge and CHIRPS rainfall data. Multi-timescale SPI analysis identified recurrent moderate to severe drought episodes, notably during 1984–1993, 1999–2004, 2009–2013, 2017, and 2022–2024. These events often coincided with the critical agricultural seasons (MAM and SON), highlighting their potential socioeconomic impacts on rain-fed farming and water supply systems. The observed wet and dry periods also broadly correspond to ENSO-related variability reported for East Africa, including conditions associated with 1983, 1998–1999, 2006, 2010–2011, and 2023–2024 (Nicholson & Kim, 1997; Omondi et al., 2013; Forster, 2025). The findings are consistent with earlier evidence of rainfall variability in southwestern Uganda (Nsubuga et al., 2014) and more recent drought assessments in Uganda (Ojara et al., 2024b). However, the superior performance of CHIRPS over CMORPH in Mbarara differs from findings reported by Kimani et al. (2017) and Omay et al. (2025). This difference highlights the need for local validation of satellite-derived rainfall products before their application in drought monitoring, as the performance of these products may vary across regions and datasets. Nevertheless, the strong agreement between CHIRPS and the ground-based observations supports its use for drought monitoring in Mbarara.

Acknowledgments

This project uses the GDAL and related libraries, which are developed by the Open Source Geospatial Foundation. We acknowledge the contributions of the GDAL developers and the OSGeo community. This work also used many Python packages, including but not limited to Pandas (McKinney et al., 2011), Xarray (Hoyer & Hamman, 2017), NumPy (Harris et al., 2020), SciPy (Virtanen et al., 2020), and Matplotlib (Hunter, 2007). The authors sincerely thank the anonymous referee for the insightful and constructive comments, which have greatly improved the quality and clarity of this work.

REFERENCES

Abramowitz, M., & Stegun, I. A. (1965). Handbook of Mathematical Functions with Formulas, Graphs, and Mathematical Tables. Dover Pub., NY, USA

Ageet, S., Fink, A. H., Maranan, M., Diem, J. E., Hartter, J., Ssali, A. L., & Ayabagabo, P. (2022). Validation of satellite rainfall estimates over equatorial East Africa. Journal

 This work is licensed under a Creative Commons Attribution 4.0 International License

Article DOI: https://doi.org/10.37284/eajenr.9.3.5790

of Hydrometeorology, 23(2), 129-151. https://doi.org/10.1175/JHM-D-21-0145.1

Akinsanola, A. A., Wenhaji, C. N., Barimalala, R., Monerie, P.-A., Dixon, R. D., Tamoffo, A. T., Adeniyi, M. O., Ongoma, V., Diallo, I., Gudoshava, M., Wainwright, C. M., James, R., Silverio, K. C., Faye, A., Nangombe, S. S., Pokam, M. W., Vondou, D. A., Hart, N. C. G., Pinto, I., Kilavi, M., Hagos, S., Rajagopal, E. N., Kolli, R. K., & Joseph, S. (2026). Modeling of precipitation over Africa: progress, challenges, and prospects. Advances in Atmospheric Sciences, 43(1), 59-86. https://doi.org/10.1007/s00376-024-4187-6

Aksu, H., & Akgül, M. A. (2020). Performance evaluation of CHIRPS satellite precipitation estimates over Turkey. Theoretical and Applied Climatology, 142(1), 71-84. https://doi.org/10.1007/s00704-020-03301-5

Anyamba, A., Tucker, C. J., & Mahoney, R. (2002). From El Niño to La Niña: Vegetation response patterns over east and southern Africa during the 1997–2000 period. Journal of Climate, 15(21), 3096-3103.

Arinaitwe, A. (2024). The dry spell: A warning for Uganda's food security. URL https://www.thekampalareport.com/money/2024060537957/the-dry-spell-a-warning-for-ugandas-food-security.html, accessed on October 16, 2025

Arrhenius, S., & Holden, E. S. (1897). On the influence of carbonic acid in the air upon the temperature of the earth. Publications of the Astronomical Society of the Pacific, 9(54), 14-24. https://doi.org/10.1086/121158

Beguería, S., Vicente-Serrano, S. M., Reig, F., & Latorre, B. (2014). Standardized precipitation evapotranspiration index (SPEI) revisited: parameter fitting, evapotranspiration models, tools, datasets and drought monitoring. International Journal of Climatology, 34(10), 3001-3023. https://doi.org/10.1002/joc.3887

Bhaga, T. D., Dube, T., Shekede, M. D., & Shoko, C. (2020). Impacts of climate variability and drought on surface water resources in Sub-Saharan Africa using remote sensing: A review. Remote Sensing, 12(24), 4184. https://doi.org/10.3390/rs12244184

Bwambale, J., & Mourad, K. A. (2022). Modelling the impact of climate change on maize yield in Victoria Nile Sub-basin, Uganda. Arabian Journal of Geosciences, 15(1), 40. https://doi.org/10. 1007/s12517-021-09309-z

Byakatonda, J., Openy, G., Sempewo, J. I., & Mucunguzi, D. B. (2021). Over a century evidence of historical and recent dryness/wetness in sub-humid areas: A Uganda, East African case. Meteorological Applications, 28(5), e2028. doi: 10.1002/met.2028

Diffenbaugh, N. S., & Burke, M. (2024). Intensification of socioeconomic impacts of climate extremes in the 21st century. Nature Climate Change 14(1):15, 15-23.

Dinku, T., Ceccato, P., Grover-Kopec, E., Lemma, M., Connor, S. J., & Ropelewski, C. F. (2007). Validation of satellite rainfall products over East Africa's complex topography. International Journal of Remote Sensing, 28(7), 1503-1526.

Dinku, T., Funk, C., Peterson, P., Maidment, R., Tadesse, T., Gadain, H., & Ceccato, P. (2018). Validation of the CHIRPS satellite rainfall estimates over eastern Africa. Quarterly Journal of the Royal Meteorological Society, 144, 292-312.

Epstein, A., Benmarhnia, T., & Weiser, S. D. (2020). Drought and illness among young children in Uganda, 2009–2012. The American journal of tropical medicine and hygiene, 102(3), 644.

Filipović, L., Putniković, S., Stosic, B., Stosic, T., Djurdjević, V., & Tošić, I. (2025). Analysis of Spatio-Temporal Characteristics of Drought in Serbia from 1961 to 2020 using SPI and SPEI. International Journal of Climatology, (7), e8803.

 This work is licensed under a Creative Commons Attribution 4.0 International License

Article DOI: https://doi.org/10.37284/eajenr.9.3.5790

Forster, P. M., Smith, C., Walsh, T., Lamb, W. F., Lamboll, R., Cassou, C., Hauser, M., Hausfather, Z., Lee, J.-Y., Palmer, M. D., von Schuckmann, K., Slangen, A. B. A., Szopa, S., Trewin, B., Yun, J., Gillett, N. P., Jenkins, S., Matthews, H. D., Raghavan, K., Ribes, A., Rogelj, J., Rosen, D., Zhang, X., Allen, M., Aleluia Reis, L., Andrew, R. M., Betts, R. A., Borger, A., Broersma, J. A., Burgess, S. N., Cheng, L., Friedlingstein, P., Domingues, C. M., Gambarini, M., Gasser, T., Gütschow, J., Ishii, M., Kadow, C., Kennedy, J., Killick, R. E., Krummel, P. B., Liné, A., Monselesan, D. P., Morice, C., Mühle, J., Naik, V., Peters, G. P., Pirani, A., Pongratz, J., Minx, J. C., Rigby, M., Rohde, R., Savita, A., Seneviratne, S. I., Thorne, P., Wells, C., Western, L. M., van der Werf, G. R., Wijffels, S. E., Masson-Delmotte, V., and Zhai, P. (2025). Indicators of Global Climate Change 2024: annual update of key indicators of the state of the climate system and human influence, Earth Syst. Sci. Data, 17, 2641–2680. https://doi.org/10.5194/essd-17-2641-2025

Funk, C., Peterson, P., Landsfeld, M., Pedreros, D., Verdin, J., Shukla, S., Husak, G., Rowland, J., Harrison, L., Hoell, A., & Michaelsen, J. (2015). The climate hazards infrared precipitation with stations—a new environmental record for monitoring extremes. Scientific data, 2(1), 150066. https://doi.org/10.1038/sdata.2015.66

Gommers, R., Virtanen, P., Haberland, M., Burovski, E., Reddy, T., Weckesser, W., Oliphant, T. E., Cournapeau, D., Nelson, A., alexbrc, Roy, P., Peterson, P., Polat, I., Wilson, J., endolith, Mayorov, N., van der Walt, S., Colley, L., Brett, M., Laxalde, D., Larson, E., Sakai, A., Millman, J., Bowhay, J., Lars, peterbell, Carey, C. J., van Mulbregt, P., eric-jones, & Striega, K. (2024). scipy/scipy: SciPy 1.15. 0. Zenodo. https://doi.org/10.5281/zenodo.14593523

Gumus, V. (2023). Evaluating the effect of the SPI and SPEI methods on drought monitoring over Turkey. J. of Hydrology, 626, 130386. https://doi.org/10.1016/j.jhydrol.2023.130386

Guttman, N. B. (1999). Accepting the standardized precipitation index: a calculation algorithm. JAWRA Journal of the American Water Resources Association, 35(2), 311-322. https://doi.org/10.1111/j.1752-1688.1999.tb03592.x

Harris, C. R., Millman, K. J., Van Der Walt, S. J., Gommers, R., Virtanen, P., Cournapeau, D., Wieser, E., Taylor, J., Berg, S., Smith, N. J., Kern, R., Picus, M., Hoyer, S., van Kerkwijk, M. H., Brett, M., Haldane, A., Fernández del Río, J., Wiebe, M., Peterson, P., Gérard-Marchant, P., Sheppard, K., Reddy, T., Weckesser, W., Abbasi, H., Gohlke, H., & Oliphant, T. E. (2020). Array programming with NumPy. nature, 585(7825), 357-362. https://doi.org/10.1038/s41586-020-2649-2

Hoyer, S., & Hamman, J. (2017). xarray: ND labeled arrays and datasets in Python. Journal of Open Research Software, 5(1), 10. https://doi.org/10.5334/jors.148

Hunter, J. D. (2007). Matplotlib: A 2D graphics environment. Computing in science & engineering, 9(3), 90-95. https://doi.org/10.1109/MCSE.2007.55

Jackson, R. B., Saunois, M., Martinez, A., Canadell, J. G., Yu, X., Li, M., Poulter, B., Raymond, P. A., Regnier, P., Ciais, P., Davis, S. J., & Patra, P. K. (2024). Human activities now fuel two-thirds of global methane emissions. Environmental Research Letters, 19(10), 101002. https://doi.org/10.1088/1748-9326/ad6463

Joyce, R. J., Janowiak, J. E., Arkin, P. A., & Xie, P. (2004). CMORPH: A method that produces global precipitation estimates from passive microwave and infrared data at high spatial and temporal resolution. Journal of Hydrometeorology, 5(3), 487-503.

Kaprom, C., Williams, J. A., Mehrotra, R., Ophaphaibun, C., & Sriwongsitanon, N. (2025). A comprehensive evaluation of the

 This work is licensed under a Creative Commons Attribution 4.0 International License

Article DOI: https://doi.org/10.37284/eajenr.9.3.5790

accuracy of satellite-based precipitation estimates over Thailand. Journal of Hydrology: Regional Studies, 59, 102380.

Kendall, M. G. (1948). Rank correlation methods. London: Charles Griffin and Co. Ltd., 42 Drury Lane. https://doi.org/10.1017/S0020268100013019

Kimani, M. W., Hoedjes, J., & Su, Z. (2017). An assessment of satellite-derived rainfall products relative to ground observations over East Africa. Remote Sensing 9 (5): 430. https://doi.org/10.3390/rs9050430

Kyatengerwa, C., Kim, D., & Choi, M. (2020). A national-scale drought assessment in Uganda based on evapotranspiration deficits from the Bouchet hypothesis. Journal of Hydrology, 580, 124348. https://doi.org/10.1016/j.jhydrol.2019.124348

Lee, H., Calvin, K., Dasgupta, D., Krinner, G., Mukherji, A., Thorne, P., Trisos, C., Romero, J., Aldunce, P., Barrett, K., Blanco, G., Cheung, W. W. L., Connors, S. L., Denton, F., Diongue-Niang, A., Dodman, D., Matthias, Garschagen, Geden, O., Hayward, B., Jones, C., Jotzo, F., Krug, T., Lasco, R., Lee, J-Y., Masson-Delmotte, V., Meinshausen, M., Mintenbeck, K., Mokssit, A., Otto, F. E. L., Pathak, M., Pirani, A., Poloczanska, E., Pörtner, H-O., Revi, A., Roberts, D. C., Roy, J., Ruane, A. C., Skea, J., Shukla, P. R., Slade, R., Slangen, A., Sokona, Y., Sörensson, A. A., Tignor, M., van Vuuren, D., Wei, Y-M., Winkler, H., Zhai, P., & Zommers Z. (2023). Climate change 2023: synthesis report. Contribution of working groups I, II and III to the sixth assessment report of the Intergovernmental Panel on Climate Change. https://doi.org/10.59327/IPCC/AR6-9789291691647

Liebmann, B., Hoerling, M. P., Funk, C., Bladé, I., Dole, R. M., Allured, D., Quan, X., Pegion, P., & Eischeid, J. K. (2014). Understanding recent eastern Horn of Africa rainfall variability and change. Journal of Climate, 27(23), 8630-8645.

Mann, H. B. (1945). Nonparametric tests against trend. Econometrica: Journal of the Econometric Society, 245-259. https://doi.org/10.2307/1907187

Maslin, M., Ramnath, R. D., Welsh, G. I., & Sisodiya, S. M. (2025). Understanding the health impacts of the climate crisis. Future Healthcare Journal, 12(1), 100240.

Masson-Delmotte, V., Zhai, P., Pirani, A., Connors, S. L., Pean, C., Berger, S., Caud, N., Chen, Y., Goldfarb, L., Gomis, M. I., Huang, M., Leitzell, K., Lonnoy, E., Matthews, J. B. R., Maycock, T. K., Waterfield, T., Yelekçi, O., Yu, R., & Zhou, B. (2023). IPC 2021. Summary for Policymakers. Climate Change 2021: The Physical Science Basis. Contribution of Working Group I to the Sixth Assessment Report of the Intergovernmental Panel on Climate Change. Technical Report. Cambridge University Press, Cambridge, United Kingdom and New York, NY, USA. https://doi.org/10.1017/9781009157896

McInerney, D., & Kempeneers, P. (2015). Open source geospatial tools. Springer International Publishing. https://doi.org/10.1007/978-3-319-01824-9

McKee, T. B., Doesken, N. J., & Kleist, J. (1993). The relationship of drought frequency and duration to time scales. In Proc. of the 8th Conference on Applied Climatology (Vol. 17, No. 22, pp. 179-183).

McKee, T. B., Doesken, N. J., & Kleist, J. (1995). Drought monitoring with multiple time scales. In Proc. of the 8th Conference on Applied Climatology (Issue:9 pp. 233-236).

McKinney, W. (2011). pandas: a foundational Python library for data analysis and statistics. Python for high performance and scientific computing, 14(9), 1-9.

Mukama, E. B., Yimer, E. A., Mbungu, W. B., Dondeyne, S., & Van Griensven, A. (2025). Evaluating the standardized and threshold based drought indices for historical drought detection in the Great Ruaha River Basin,

 This work is licensed under a Creative Commons Attribution 4.0 International License

Article DOI: https://doi.org/10.37284/eajenr.9.3.5790

Tanzania. Natural Hazards, 121(10), 12243-12273. https://doi.org/10.1007/s11069-025-07279-z

Mulinde, C., Twinomuhangi, R., Majaliwa, J. G. M., Waiswa, D., Mfitumukiza, D., Tumwine, F., Nakyagaba, W. N., & Asiimwe, J. (2025). Climate patterns and extremes in Uganda's Arabica and Robusta coffee regions. African Geographical Review, 1-23.

Mungul, V., & Nowbuth, M. D. (2025). Comparative study of SPI and SPEI drought indices for meteorological drought assessment in Mauritius. Jàmbá: Journal of Disaster Risk Studies, 17(2), 1-12. https://doi.org/10.4102/jamba.v17i2.1748

Nansamba, M., Sibiya, J., Tumuhimbise, R., Ocimati, W., Kikulwe, E., Karamura, D., & Karamura, E. (2022). Assessing drought effects on banana production and on-farm coping strategies by farmers—A study in the cattle corridor of Uganda. Climatic Change, 173(3), 21. https://doi.org/10.1007/s10584-022-03408-w

Tenywa, G. (2007). Climate change hits Uganda. The New Vision (April 7, 2007). https://www.newvision.co.ug/news/1167515/climate-change-hits-uganda

Ngoma, H., Wen, W., Ojara, M., & Ayugi, B. (2021). Assessing current and future spatiotemporal precipitation variability and trends over Uganda, East Africa, based on CHIRPS and regional climate model datasets. Meteorology and Atmospheric Physics, 133(3), 823-843. https://doi.org/10.1007/s00703-021-00784-3

Nicholson, S. E. (2015). Long-term variability of the East African 'short rains' and its links to large-scale factors. International Journal of Climatology, 35(13), 3979. https://doi.org/10.1002/joc.4259

Nicholson, S. E. (2017). Climate and climatic variability of rainfall over eastern Africa. Reviews of Geophysics, 55(3), 590-635. https://doi.org/10.1002/2016RG000544

Nicholson, S. E., & Kim, J. (1997). The relationship of the El Niño–Southern Oscillation to African rainfall. International Journal of Climatology: A Journal of the Royal Meteorological Society, 17(2), 117-135.

Nsubuga, F. N. W., Olwoch, J. M., Rautenbach, C. D., & Botai, O. J. (2014). Analysis of mid-twentieth century rainfall trends and variability over southwestern Uganda. Theoretical and Applied Climatology, 115(1), 53-71. https://doi.org/10.1007/s00704-013-0864-6

Nsubuga, F. W., & Rautenbach, H. (2018). Climate change and variability: a review of what is known and ought to be known for Uganda. International Journal of Climate Change Strategies and Management, 10(5), 752-771.

Ojara, M. A., Babaousmail, H., Aribo, L., Namumbya, S., Mumo, L., & Ogwang, B. A. (2024a). Patterns of rainfall and temperature and their relationships with potential evapotranspiration rates over the period 1981–2022 in parts of central, western, southern, and southwestern Uganda. Environmental Monitoring and Assessment, 196(10), 898. https://doi.org/10.1007/s10661-024-12991-7

Ojara, M. A., Namumbya, S., Ogwang, B. A., & Limbu, P. T. (2024b). Regional and farm level droughts characteristics for southwestern Uganda during 1981–2017. Soil Security, 15, 100148. https://doi.org/10.1016/j.soisec.2024.100148

Okirya, M., & Du Plessis, J. A. (2024). Trend and variability analysis of annual maximum rainfall using observed and remotely sensed data in the tropical climate zones of Uganda. Sustainability, 16(14), 6081. https://doi.org/10.3390/su16146081

Omay, P. O., Muthama, N. J., Oludhe, C., Kinama, J. M., Artan, G., & Atheru, Z. (2023). Changes and variability in rainfall

 This work is licensed under a Creative Commons Attribution 4.0 International License

Article DOI: https://doi.org/10.37284/eajenr.9.3.5790

onset, cessation, and length of rainy season in the IGAD region of Eastern Africa. Theoretical and Applied Climatology, 152(1), 871-893. https://doi.org/10.1007/s00704-023-04433-0

Omay, P. O., Muthama, N. J., Oludhe, C., Kinama, J. M., Artan, G., & Atheru, Z. (2025). Evaluation of satellite-based rainfall estimates over the IGAD region of Eastern Africa. Meteorology and Atmospheric Physics, 137(2), 22. https://doi.org/10.1007/s00703-025-01068-w

Omondi, P., Awange, J. L., Ogallo, L. A., Ininda, J., & Forootan, E. (2013). The influence of low frequency sea surface temperature modes on delineated decadal rainfall zones in Eastern Africa region. Advances in Water Resources, 54, 161-180.

Owoyesigire, B., Mpairwe, D., Ericksen, P., & Peden, D. (2016). Trends in variability and extremes of rainfall and temperature in the cattle corridor of Uganda. Uganda Journal of Agricultural Sciences, 17(2), 231-244. https://doi.org/10.4314/ujas.v17i2.8

Palmer, P. I., Wainwright, C. M., Dong, B., Maidment, R. I., Wheeler, K. G., Gedney, N., Hickman, J. E., Madani, N., Folwell, S. S., Abdo, G., Allan, R. P., Black, E. C. L., Feng, L., Gudoshava, M., Haines, K., Huntingford, C., Kilavi, M., Lunt, M. F., Shaaban, A., & Turner, A. G. (2023). Drivers and impacts of Eastern African rainfall variability. Nature Reviews Earth & Environment, 4(4), 254-270.

Ripple, W. J., Wolf, C., Gregg, J. W., Rockström, J., Newsome, T. M., Law, B. E., Marques, L., Lenton, T. M., Xu, C., Huq, S., Simons, L., & King, S. D. A. (2023). The 2023 state of the climate report: Entering uncharted territory. BioScience, 73(12), 841-850. https://doi.org/10.1093/biosci/biad080

Ripple, W. J., Wolf, C., Gregg, J. W., Rockström, J., Mann, M. E., Oreskes, N., Lenton, T. M., Rahmstorf, S., Newsome, T. M., Xu, C., Svenning, J-C, Pereira, C. C., Law, B. E., & Crowther, T. W. (2024). The 2024 state of the climate report: Perilous times on planet Earth. BioScience, 74(12), 812-824. https://doi.org/10.1093/biosci/biae087

Rouault, E., Warmerdam, F., Schwehr, K., Kiselev, A., Butler, H., Łoskot, M., Szekeres, T., Tourigny, E., Landa, M., Miara, I., Elliston, B., Chaitanya, K., Plesea, L., Morissette, D., Jolma, A., Dawson, N., Baston, D., de Stigter, C., & Miura, H. (2026). GDAL/OGR Geospatial Data Abstraction Software Library. https://doi.org/10.5281/zenodo.5884351

Samal, A., Sahu, S. K., Mishra, A., Mangaraj, P., Pani, S. K., & Beig, G. (2024). Assessment and quantification of methane emission from Indian livestock and manure management. Aerosol and Air Quality Research, 24(6), 230204. https://doi.org/10.4209/aaqr.230204

Ssembajwe, R., Mulinde, C., Ddumba, S. D., Kagezi, G. H., Opio, R., Kobusinge, J., Mugagga, F., Bamutaze, Y., Gidudu, A., Arinaitwe, G., & Voda, M. (2025). Dynamics and associations of selected agrometeorological variables in Robusta growing regions of Uganda. Agricultural Water Management, 307, 109257.

Sen, P. K. (1968). Estimates of the regression coefficient based on Kendall's tau. Journal of the American Statistical Association, 63(324), 1379-1389. https://doi.org/10.2307/2285891

Ssentongo, P., Fronterre, C., Ericson, J. E., Wang, M., Al-Shaar, L., Greatrex, H., Omadi, P. O., Muvawala, J., Greybush, S. J., Mbabazi, P. K., Murray-Kolb, L. E., Muwanguzi, A. J. B., & Schiff, S. J. (2025). Preconception and prenatal environment and growth faltering among children in Uganda. JAMA Network Open, 8(3), e251122.

Stagge, J. H., Tallaksen, L. M., Gudmundsson, L., Van Loon, A. F., & Stahl, K. (2015). Candidate distributions for climatological

 This work is licensed under a Creative Commons Attribution 4.0 International License

Article DOI: https://doi.org/10.37284/eajenr.9.3.5790

drought indices (SPI and SPEI). International Journal of Climatology, 35(13), 4027-4040. https://doi.org/10.1002/joc.4267

Theil, H. (1950). A rank-invariant method of linear and polynomial regression analysis. Indagationes mathematicae, 12(85), 173. https://doi.org/10.1007/978-94-011-2546-8_20

Twongyirwe, R., Mfitumukiza, D., Barasa, B., Naggayi, B. R., Odongo, H., Nyakato, V., & Mutoni, G. (2019). Perceived effects of drought on household food security in South-western Uganda: Coping responses and determinants. Weather and Climate Extremes, 24, 100201. https://doi.org/10.1016/j.wace.2019.100201

van Asten, P. J., Fermont, A. M., & Taulya, G. (2011). Drought is a major yield loss factor for rainfed East African highland banana. Agricultural Water Management, 98(4), 541-552.

Vautard, R., Cattiaux, J., Happé, T., Singh, J., Bonnet, R., Cassou, C., Coumou, D., D'Andrea, F., Faranda, D., Fischer, E., Ribes, A., Sippel S., & Yiou, P. (2023). Heat extremes in Western Europe increasing faster than simulated due to atmospheric circulation trends. Nature Communications, 14(1), 6803. https://doi.org/10.1038/s41467-023-42143-3

Vicente-Serrano, S. M., Beguería, S., & López-Moreno, J. I. (2010). A multiscalar drought index sensitive to global warming: the standardized precipitation evapotranspiration index. Journal of Climate, 23(7), 1696-1718. https://doi.org/10.1175/2009JCLI2909.1

Virtanen, P., Gommers, R., Oliphant, T. E., Haberland, M., Reddy, T., Cournapeau, D., Burovski, E., Peterson, P., Weckesser, W., Bright, J., van der Walt, S. J., Brett, M., Wilson, K. J., Millman, J., Mayorov, N., Nelson, A. R. J., Jones, E., Kern, R., Larson, E., Carey, C. J., Polat İlhan, Feng, Y., Moore, E. W., VanderPlas, J. (2020). SciPy 1.0: fundamental algorithms for scientific computing in Python. Nature Methods, 17(3), 261-272. https://doi.org/10. 1038/s41592-019-0686-2

Wang, P., Asare, E. O., Pitzer, V. E., Dubrow, R., & Chen, K. (2023). Floods and diarrhea risk in young children in low- and middle-income countries. JAMA Pediatrics, 177(11), 1206-1214. https://doi.org/10.1001/jamapediatrics.2023.3964

Warmerdam, F. (2008). The geospatial data abstraction library. In: Open source approaches in spatial data handling. Springer, p 87-104, https://doi.org/10.1007/978-3-540-74831-1_5

Whitaker, J., Filipe, Khrulev, C., Hill, P., Huard, D., Hoyer, S., Taves, M., Pastewka, L., Mohr, A., Marquardt, C., Couwenberg, B., Paulik, C., Cuntz, M., Roet, S., Whitaker, J., Bohnet, M., Brett, M., Korenčiak, M., Hetland, R., Barna, A., Helmus, J. J., Harfouche, M., Henderson, B. H., fredrik, Bekozi, Rothenpieler, T., Kluyver, T., bluppfisk, May, R. (2024). Unidata/netcdf4-python: version 1.7.1 release. https://doi.org/10.5281/zenodo.12549797

van der Wiel, K., & Bintanja, R. (2021). Contribution of climatic changes in mean and variability to monthly temperature and precipitation extremes. Communications Earth & Environment, 2(1), 1. https://doi.org/10.1038/s43247-020-00077-4

Xie, P., Joyce, R., Wu, S., Yoo, S. H., Yarosh, Y., Sun, F., & Lin, R. (2017). Reprocessed, bias-corrected CMORPH global high-resolution precipitation estimates from 1998. Journal of Hydrometeorology, 18(6), 1617-1641. https://doi.org/10.1175/JHM-D-16-0168.1

 This work is licensed under a Creative Commons Attribution 4.0 International License