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Spatiotemporal Variability of Rainfall Trends and Influencing Factors in Tanzania

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Abstract

Rainfall variability strongly influences water availability, agriculture, and social and economic development in Tanzania, where most livelihoods depend on rain-fed farming. Understanding how rainfall varies across space and time and recognizing its driving factors are therefore essential for cultivating climate monitoring and resource management. This study examines the spatiotemporal variability of rainfall trends in Tanzania and their relationship with global sea surface temperature patterns during the period 1979-2024. Rainfall data were obtained from the European Centre for Medium-Range Weather Forecasts reanalysis dataset, while global sea surface temperature data were obtained from the National Oceanic and Atmospheric Administration. Several statistical methods were applied to evaluate rainfall variability and trends, including standardized anomaly analysis, the Mann-Kendall trend test with Sen's slope estimator, empirical orthogonal function analysis, and correlation analysis. The results reveal pronounced spatial variability in rainfall across the country, with higher rainfall amounts occurring in the Lake Victoria basin and coastal regions and lower rainfall over the central plateau. Tanzania displays both bimodal rainfall patterns in northern and eastern regions and a unimodal rainfall regime in southern areas. Trend analysis indicates generally weak and spatially heterogeneous rainfall trends, with slight decreasing tendencies in parts of northwestern Tanzania. Temporal analysis highlights strong inter-annual variability, with wet years such as 1983, 1998, 2018, and 2023 and dry conditions during 1993, 2003, and 2005. The dominant spatial mode of rainfall variability explains about 42.5% of the variance during the long rains season and about 69.1% during the short rains season. Correlation analysis indicates that rainfall variability is influenced by sea surface temperature disparities in the tropical Pacific and Indian Oceans, suggesting the influence of large-scale ocean-atmosphere interactions. These findings provide insights that may support improved climate forecasting and sustainable management of water and agricultural resources in Tanzania.

Keywords

Spatiotemporal Rainfall Variability, Rainfall Trends, Sea Surface Temperature, Climate Variability, Tanzania

1. Introduction

Rainfall variability is a major component of the global climate system because of its influence on ecosystems, agriculture, water resources and socio-economic development. Variations in precipitation patterns can significantly affect hydrological cycles, crop productivity and freshwater availability across many countries of the world (Held & Soden, 2006; Trenberth et al., 2014). Over recent years, increasing climate variability has intensified the occurrence of extreme precipitation events such as floods and droughts posing serious challenges for sustainable development and environmental management (Alexander et al., 2006). Global precipitation variability is influenced by complex interactions between atmospheric circulation, ocean-atmospheric circulation ocean atmospheric dynamics and land atmospheric feedback processes (Allan et al., 2020). Large-scale climate modes including the El Nino-Southern Oscillation (ENSO), the Indian Ocean Dipole (IOD) and the Pacific Decadal Oscillation (PDO) play a big role in modulating rainfall variability across different regions through atmospheric teleconnections (Santoso et al., 2020). These climate modes influence atmospheric circulation and moisture transport producing rainfall anomalies across many parts of the world (Trenberth et al., 2014; Santoso et al., 2020). Consequently, understanding the spatial and temporal variability of rainfall and its relationship with large scale ocean-atmosphere interactions has become an important focus in climate research. Such knowledge is essential for improving climate prediction and disaster risk management, and climate adaptation strategies (Alexander et al., 2006; Legg, 2021).

Rainfall variability is particularly important in Africa because the continent's agriculture and water resources depend heavily on rainfall. Many African countries rely on rain-fed agriculture systems, making them highly vulnerable to fluctuations in rainfall patterns (Funk, Peterson et al., 2015; Nicholson et al., 2018). Africa has the rainfall climate which is primarily controlled by the seasonal migration of the ITCZ, which governs the distribution and timing of rainfall across the continent (Dunning et al., 2016; Nicholson et al., 2018). In addition to the ITCZ, rainfall variability is influenced by regional atmospheric circulation systems and interactions with surrounding oceans, including the Atlantic and Indian Oceans (Lyon & DeWitt, 2012; Nicholson et al., 2018). Large-scale climate phenomena such as ENSO and the Indian Ocean Dipole further modulate rainfall variability across Africa by altering atmospheric circulation patterns and moisture transport (Nicholson & Kim, 1997; Tierney et al., 2015). In East Africa, rainfall variability has been associated with complex interactions between the Indian Ocean, Pacific Ocean, and regional atmospheric dynamics (Black et al., 2004; Funk, Shukla et al., 2015). For instance, positive phases of the Indian Ocean Dipole are often linked to warmer sea surface temperatures in the western Indian Ocean and enhanced rainfall during the October-December short rains season in East Africa (Saji et al., 1999; Black et al., 2003). ENSO events also influence rainfall variability in the region by modifying atmospheric circulation and moisture convergence (Nicholson & Kim, 1997; Lyon & DeWitt, 2012). Despite these advances, uncertainties remain regarding the spatial distribution and long-term variability of rainfall across different parts of Africa, particularly in regions with complex climate influences (Funk, Shukla et al., 2015; Nicholson et al., 2018).

Tanzania, located in East Africa between the Indian Ocean and the central African plateau, exhibits complex rainfall patterns influenced by regional topography, atmospheric circulation, and ocean-atmosphere interactions. The country experiences significant spatial and temporal variability in rainfall due to factors such as altitude, distance from the coast, and seasonal atmospheric circulation patterns (Nicholson, 2018). Tanzania is characterized by both bimodal and unimodal rainfall regimes depending on geographical location. Northern and eastern regions of the country, including coastal areas and regions around Lake Victoria, generally experience a bimodal rainfall pattern consisting of the long rains March to May (MAM) and the short rains October to December (OND) (Nicholson, 2018). In contrast, much of southern, western, and central Tanzania experiences a unimodal rainfall regime, with a single rainy season occurring between November and April (Paeth et al., 2017; Nicholson, 2018). These rainfall regimes are strongly influenced by the seasonal migration of the ITCZ and regional atmospheric circulation over the Indian Ocean (Dunning et al., 2016; Nicholson, 2018). Rainfall variability in Tanzania has important implications for agriculture, hydropower generation, and water resource management (Paeth et al., 2017). Previous studies have shown that large-scale climate drivers such as ENSO and the Indian Ocean Dipole significantly influence rainfall variability in Tanzania and the broader East African region (Nicholson & Kim, 1997; Ongoma et al., 2018). IOD events are frequently associated with enhanced rainfall during the OND season, while ENSO events may influence rainfall patterns through changes in atmospheric circulation and moisture transport (Saji et al., 1999; Black et al., 2003; Tierney et al., 2015). However, the spatial structure and dominant modes of rainfall variability across Tanzania remain insufficiently explored, particularly using long-term datasets and advanced statistical techniques such as Empirical Orthogonal Function (EOF) analysis (Hannachi et al., 2007). Despite the growing body of research on rainfall variability in East Africa, several research gaps remain. Many previous studies have focused primarily on seasonal rainfall variability without fully examining the combined spatial and temporal characteristics of rainfall across multiple time scales. In addition, relatively few studies have analyzed the dominant spatial modes of rainfall variability across Tanzania using long-term observational datasets and advanced statistical techniques (Hannachi et al., 2007). Furthermore, although ENSO and the Indian Ocean Dipole are recognized as major drivers of rainfall variability in East Africa, their spatial teleconnections with rainfall patterns over Tanzania remain insufficiently quantified (Tierney et al., 2015; Ongoma et al., 2018). Addressing these gaps is essential for improving understanding of rainfall variability and its linkages with global climate systems. Therefore, this study investigates the spatiotemporal variability of rainfall over Tanzania during the period 1979-2024 using satellite and reanalysis datasets. Specifically, the study aims 1) Analyze the spatial and temporal variability of rainfall over Tanzania during the period 1979-2024 at annual, seasonal (MAM and OND), and monthly time scales, 2) identify the dominant spatial modes of rainfall variability using Empirical Orthogonal Function analysis, and 3) to examine the relationship between Tanzania rainfall variability and global sea surface temperature anomalies. By integrating rainfall variability analysis with global SST-rainfall correlations, this research seeks to improve understanding of the large-scale climate drivers influencing rainfall patterns in Tanzania and contribute to enhanced climate monitoring and prediction for the region.

2. Data and Methods

2.1. Study Area

Tanzania is located in East Africa between approximately 12˚S-0˚ latitudes and 29˚E-42˚E longitude, bordering Kenya and Uganda to the north, Rwanda, Burundi and the Democratic Republic of Congo to the west, Zambia, Malawi and Mozambique to the south, and the Indian Ocean to the east (**Figure 1**). The country covers an area of about 945,000 km^2, making it one of the largest countries in East Africa (URT, 2013). Tanzania has a diverse topography consisting of coastal plains, central plateaus, mountainous highlands, and large inland lakes, including Lake Victoria, Lake Tanganyika, and Lake Nyasa (Lake Malawi). Elevation ranges from sea level along the Indian Ocean coast to about 5895 m at Mount Kilimanjaro, the highest mountain in Africa (Paeth et al., 2017; Nicholson, 2018). The central plateau generally lies between 900 and 1200 m above sea level, while the northern and southern highlands contain mountainous regions that significantly influence regional climate patterns (Nicholson, 2018).

The climate of Tanzania is predominantly tropical, but it varies spatially due to differences in altitude, distance from the ocean, and regional atmospheric circulation. The country experiences both bimodal and unimodal rainfall regimes, largely controlled by the seasonal migration of the Intertropical Convergence Zone (ITCZ) (Dunning et al., 2016; Nicholson, 2018). Northern and eastern regions, including the coastal areas and regions around Lake Victoria, generally experience a bimodal rainfall pattern consisting of the long rains (MAM) and the short rains (OND). In contrast, the southern, western, and central parts of Tanzania experience a unimodal rainfall regime, with a single rainy season occurring between November and April (Paeth et al., 2017).

Rainfall distribution across Tanzania varies considerably from region to region. Coastal areas and regions near Lake Victoria receive relatively high rainfall, often exceeding 1200 mm annually, while semi-arid areas of the central plateau may receive less than 600 mm per year. Rainfall variability in Tanzania is influenced by several regional and large-scale climate systems, including the seasonal movement of the ITCZ, moisture transport from the Indian Ocean, and large-scale climate model such as the El Niño-Southern Oscillation (ENSO) and the Indian Ocean Dipole (IOD) (Nicholson & Kim, 1997; Saji et al., 1999). These climatic drivers contribute to substantial inter-annual and seasonal rainfall variability, which has important implications for agriculture, water resources, and hydropower generation in the country.

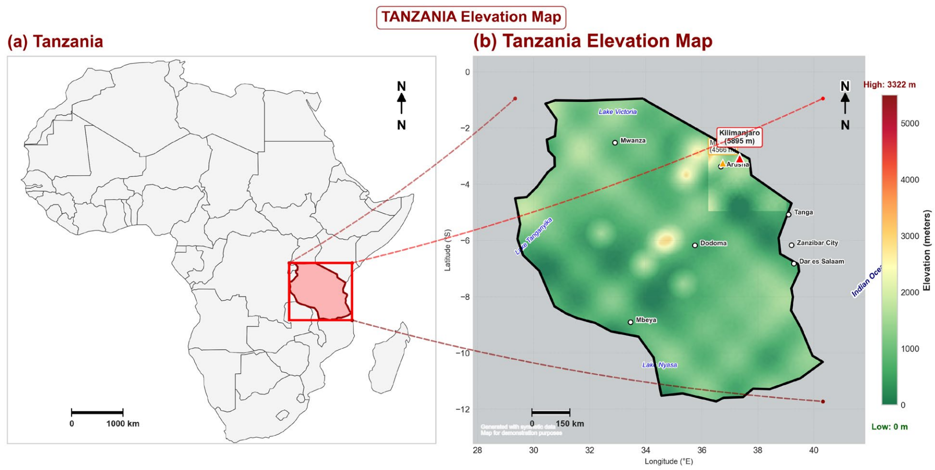

Figure 1. (a) Location of Tanzania within Africa, with the country highlighted; (b) Elevation map of Tanzania showing major cities and key features including Mt. Kilimanjaro and major lakes.

2.2. Dataset

This study uses long-term gridded climate datasets to investigate rainfall variability over Tanzania and its relationship with global sea surface temperature (SST) anomalies during the period 1979-2024. Two primary datasets were used: ERA5 reanalysis rainfall data and global sea surface temperature data obtained from the National Oceanic and Atmospheric Administration (NOAA). Rainfall data were obtained from the ERA5 reanalysis dataset produced by the European Centre for Medium-Range Weather Forecasts (ECMWF). ERA5 provides globally consistent atmospheric and surface variables generated through advanced data assimilation and numerical weather prediction models (Hersbach et al., 2020). In this study, the total precipitation (tp) variable was used to represent rainfall over Tanzania. The dataset has a spatial resolution of approximately 0.25° × 0.25° and provides high temporal resolution precipitation data that were aggregated to daily totals and subsequently used to compute monthly, seasonal, and annual rainfall totals. ERA5 precipitation data have been widely validated over East Africa and shown to provide reliable representation of rainfall variability, with performance comparable to gauge-adjusted datasets such as CHIRPS, particularly in capturing seasonal and interannual variability (Funk, Shukla et al., 2015; Tarek et al., 2020). ERA5 reanalysis products have been widely used in climate variability and hydrological studies because of their reliability, global coverage, and improved representation of atmospheric processes (Hersbach et al., 2020; Tarek et al., 2020). The rainfall data were extracted for the period 1979-2024 and spatially limited to Tanzania using the national boundary shape file obtained from the Global Administrative Areas (GADM) database, ensuring that the analysis represents rainfall conditions within the study area.

To investigate the influence of large-scale oceanic processes on rainfall variability, global sea surface temperature (SST) data were obtained from the National Oceanic and Atmospheric Administration (NOAA). SST datasets produced by NOAA provide globally consistent observations of ocean temperature and are widely used in climate variability studies (Huang et al., 2017). This dataset provides globally gridded monthly SST fields at a spatial resolution of 2˚ × 2˚ and covers the period 1979-2024 widely used for climate variability and teleconnection studies. SST anomalies were computed relative to the standard 1981-2010 climatological reference period, following common practice in climate analysis. Sea surface temperature plays an important role in modulating atmospheric circulation and precipitation patterns through large-scale climate model such as the El Niño-Southern Oscillation (ENSO) and the Indian Ocean Dipole (IOD) (Trenberth et al., 2014; McPhaden et al., 2020). Seasonal and annual SST averages were calculated to examine their relationship with rainfall variability over Tanzania, particularly during the long rains season (MAM) and the short rains season (OND), which are the dominant rainfall seasons in the region.

2.3. Statistical Methods

To investigate rainfall variability and its relationship with global sea surface temperature anomalies, several statistical methods were applied. These include standardized anomaly analysis, the Mann-Kendall trend test, Empirical Orthogonal Function (EOF) analysis, and correlation analysis. These methods are widely used in climate variability studies to identify temporal trends, spatial variability patterns, and relationships between climatic variables (Hannachi et al., 2007). Monthly, seasonal, and annual rainfall anomalies were computed relative to a climatological baseline period of 1981-2010, which is commonly used in climate studies. For each grid cell, anomalies were calculated as the difference between the observed rainfall value and the long-term mean for the corresponding month, season, or year within the baseline period. Tanzania-wide rainfall averages were obtained by first masking the gridded rainfall data using the national boundary shapefile and then computing the spatial mean across all grid cells within the study area. The spatial averaging was performed using a simple arithmetic mean without applying grid-cell area weighting, given the relatively fine spatial resolution of the dataset. While this approach provides a reasonable representation of area-averaged rainfall, it may introduce minor biases associated with latitudinal differences in grid-cell size.

2.3.1. Standardized Anomaly

Standardized anomaly analysis was used to examine inter-annual rainfall variability over Tanzania. This method allows comparison of rainfall anomalies relative to the long-term climatological mean by removing the influence of different magnitudes and units. The standardized anomaly (SA) is calculated as:

$$SA_i = \frac{X_i - \overline{X}}{\delta} \tag{1}$$

where:

SA_i = Standardized anomaly for year i,

X_i = rainfall value in year i,

$\overline{X}$ = long-term mean rainfall,

δ = standard deviation of the rainfall series.

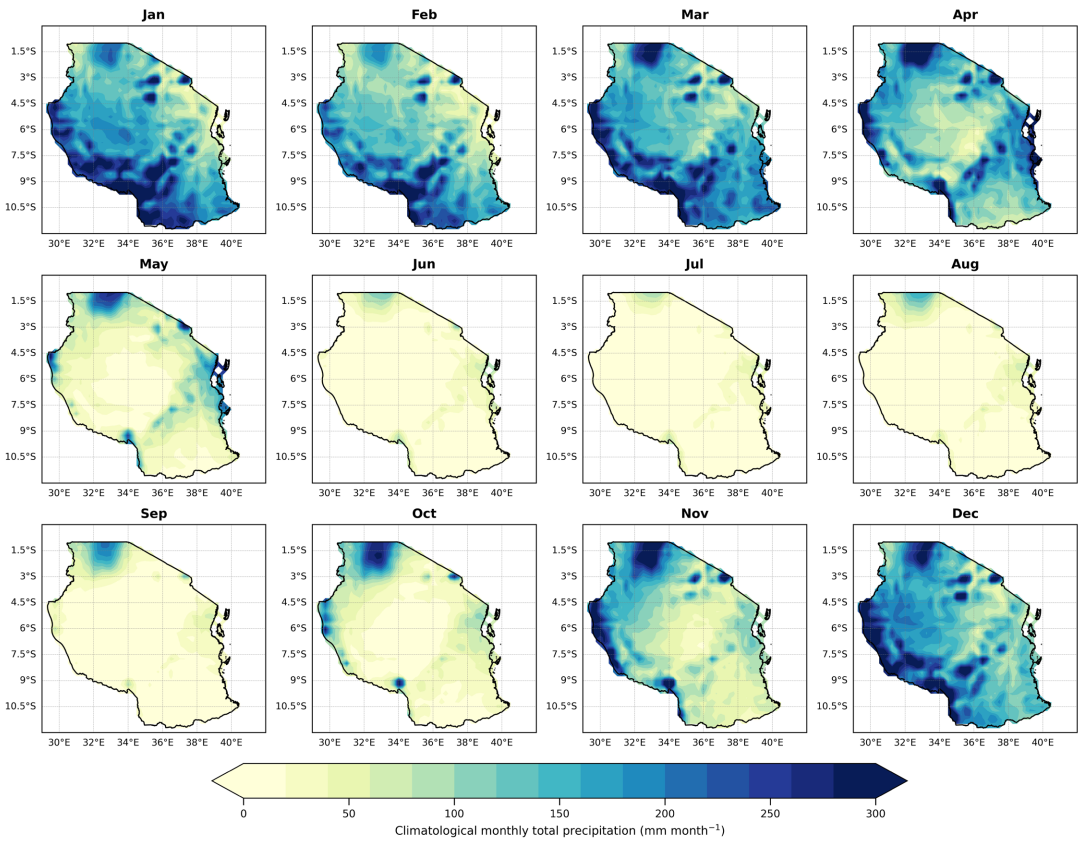

Figure 2. Spatial distribution of climatological monthly total precipitation over Tanzania for January-December, computed as the mean of annual monthly totals from the study period.

Positive standardized anomaly values indicate above-normal rainfall conditions, whereas negative values indicate below-normal rainfall conditions (Nicholson, 2018). This method is commonly used in rainfall variability studies to identify wet and dry years.

2.3.2. Mann-Kendal (MK) Trend Test

The Mann-Kendall (MK) test is a non-parametric statistical method widely used to detect monotonic trends in hydro-climatic time series without assuming a specific data distribution (Mann, 1945). It is particularly suitable for climate data because it is robust against outliers and non-normal distributions.

The MK test statistic S is calculated as

$$S = \sum_{i=1}^{n-1} \sum_{j=i+1}^{n} \operatorname{sgn}\left(x_j - x_i\right) \tag{2}$$

$$\operatorname{sgn}\left(x_j - x_i\right) = \begin{cases} 1, \text{if } x_j - x_i > 0 \\ 0, \text{if } x_j - x_i = 0 \\ -1, \text{if } x_j - x_i < 0 \end{cases} \tag{3}$$

The variance S is given by:

$$\operatorname{var}(S) = \frac{n(n-1)(2n+5)}{18} \tag{4}$$

The standardized test statistic Z is then calculated as:

$$Z = \begin{cases} \dfrac{s-1}{\sqrt{\operatorname{var}(s)}}, S > 0 \\ 0, S = 0 \\ \dfrac{s+1}{\sqrt{\operatorname{var}(s)}}, S < 0 \end{cases} \tag{5}$$

A positive Z value indicates an increasing trend, while a negative Z value indicates a decreasing trend. The significance of the trend is evaluated using a 95% confidence level ($p < 0.05$).

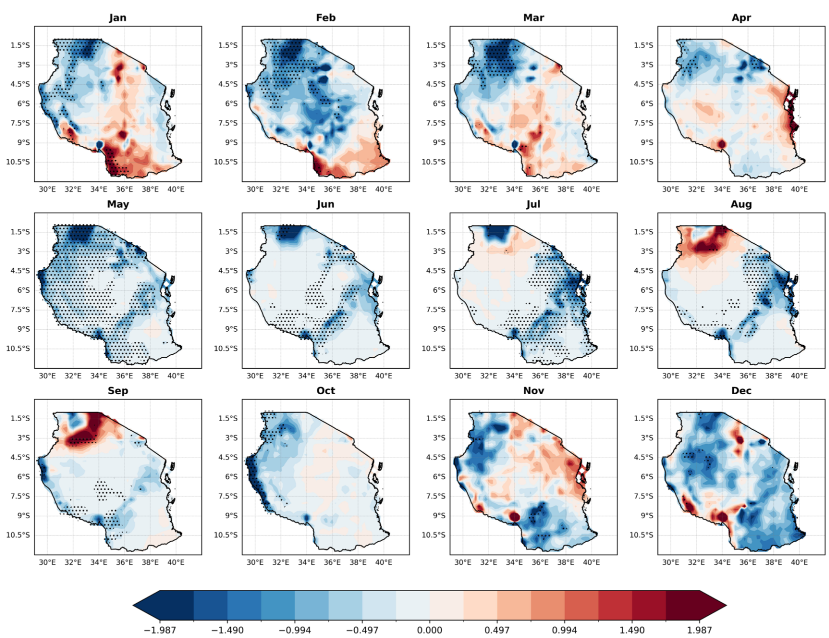

Figure 3. Spatial patterns of monthly rainfall trends over Tanzania for 1979-2024, expressed as linear trends in monthly totals (mm·month^{-1}·year^{-1}).

2.3.3. Empirical Orthogonal Functions (EOF)

Empirical Orthogonal Function (EOF) analysis was applied to identify the dominant spatial patterns of rainfall variability across Tanzania. The analysis was performed separately for the long rains season (March-May, MAM) and the short rains season (October-December, OND) to capture season-specific variability patterns. Prior to the EOF computation, seasonal rainfall totals were first calculated and then converted into anomalies by removing the long-term mean (1981-2010 baseline). The anomaly fields were not further standardized, as the analysis focused on preserving the original variance structure of rainfall variability. To account for the effect of latitudinal differences in grid-cell area, spatial weighting based on the square root of the cosine of latitude was applied before performing the EOF decomposition. This weighting ensures that higher-latitude grid cells do not exert disproportionate influence on the resulting modes. EOF analysis decomposes a spatiotemporal dataset into orthogonal spatial patterns (EOF modes) and their corresponding temporal coefficients known as principal components (PCs) (Hannachi et al., 2007).

The rainfall anomaly field $X(x,t)$ can be expressed as:

$$X(x,t)=\sum_{k=1}^{m} PC_k(t)\times EOF_k(x) \tag{6}$$

$X(x,t)$ = rainfall anomaly at location x and time t,

$EOF_k(x)$ = spatial pattern of k^{th} EOF mode,

$PC_k(t)$ = principal component representing temporal variability,

m = number of modes,

The fraction of total variance explained by each EOF mode is calculated as:

$$VF_k=\frac{\lambda_k}{\sum_{i-1}^{n}\lambda_i}\times 100 \tag{7}$$

VF_k = variance explained by the k^{th} mode,

λ_k = eigenvalue of the k^{th} mode.

EOF analysis is widely used in climate research to identify dominant modes of climate variability and to understand spatial rainfall patterns (Hannachi et al., 2007).

2.3.4. Correlation Analysis

Correlation analysis was performed to examine the relationship between rainfall variability over Tanzania and global sea surface temperature anomalies. The Pearson correlation coefficient was used to quantify the strength and direction of the linear relationship between rainfall anomalies and SST anomalies. The Pearson correlation coefficient r is defined as:

$$r\frac{\sum_{i=1}^{n}(x_i-\bar{x})(y_i-\bar{y})}{\sqrt{\sum_{i=1}^{n}(x_i-\bar{x})^2\sum_{i=1}^{n}(y_i-\bar{y})^2}} \tag{8}$$

where: x_i = rainfall anomaly for year i

y_i = SST anomaly for year i

$\overline{x}$ and $\overline{y}$ = mean values

n = number of observations

The statistical significance of the correlation was evaluated using the Student's t-test, defined as:

$$t = r\sqrt{\frac{n-2}{1-r^2}} \tag{9}$$

where n represents the number of observations. Correlations were considered statistically significant at the 95% confidence level ($p < 0.05$).

In addition to the correlation coefficient, the Root Mean Square Error (RMSE) was calculated to quantify the magnitude of differences between rainfall anomalies and SST-related variability. RMSE provides a measure of the average error magnitude and is widely used in climate data analysis. RMSE is expressed as:

$$\text{RMSE} = \sqrt{\frac{1}{n}\sum_{i=1}^{n}\left(x_i - y_i\right)^2} \tag{10}$$

x_i = observed rainfall anomaly,

y_i = corresponding SST related value,

n = number of observations.

3. Results and Discussion

3.1. Spatial Distribution of Rainfall

The spatial distribution of climatological rainfall over Tanzania during 1979-2024 shows pronounced spatial variability across the country (**Figure 2**). The annual rainfall map indicates that the highest rainfall amounts occur in the northwestern region near Lake Victoria, where annual totals exceed 2400 - 2800 mm, while moderate rainfall (approximately 1000 - 1600 mm) is observed along the coastal regions and northeastern highlands. In contrast, the central plateau, including areas around Dodoma and Singida, experiences substantially lower rainfall amounts ranging between 400 and 800 mm per year. These patterns reflect the combined influence of lake-atmosphere interactions, topography, and proximity to the Indian Ocean moisture source (Paeth et al., 2017; Nicholson, 2018).

Seasonally, rainfall distribution differs significantly between the long rains (MAM) and short rains (OND) seasons. During the MAM season, rainfall intensifies over large portions of the country, particularly in the Lake Victoria basin and northeastern Tanzania, where seasonal totals exceed 900 mm. The OND season exhibits a similar spatial pattern but generally lower rainfall totals compared with MAM, although the Lake Victoria region still experiences rainfall exceeding 700 - 900 mm. The central and southeastern regions remain comparatively drier during both seasons. These spatial patterns reflect the seasonal migration of the Intertropical Convergence Zone (ITCZ), which controls rainfall distribution across East Africa (Dunning et al., 2016; Nicholson, 2018).

Monthly climatology further reveals the bimodal rainfall structure in northern

Tanzania. Rainfall increases during March and April, with April representing the peak of the long rains, where precipitation exceeds 250 - 300 mm per month in the Lake Victoria basin. Rainfall decreases sharply during the dry season months (June-September), when most regions receive less than 50 mm per month, before increasing again during the short rains season (October-December), particularly in November and December (Figure 2). This seasonal pattern is consistent with previous studies describing the bimodal rainfall regime in northern and eastern Tanzania and the unimodal rainfall regime in the southern regions (Nicholson, 2018).

3.2. Mann-Kendall and Sen's Slope Spatial Pattern over the Study Domain

The spatial patterns of rainfall trends derived from the Mann-Kendall (MK) test and Sen's slope estimator are presented in Figure 3. The results indicate that rainfall trends across Tanzania are generally weak and spatially heterogeneous. For annual rainfall, most areas exhibit negative trends ranging between −4 and −13 mm per year, particularly over the northwestern region near Lake Victoria, where statistically significant decreasing trends are detected. In contrast, small positive trends are observed in parts of southern Tanzania, although these trends are generally weak.

Seasonally, the MAM rainfall trend also shows predominantly negative values across much of the country, especially in the northwestern regions, suggesting a gradual decline in the long rains over the study period as illustrated in Figure 4. This finding is consistent with several studies reporting a decline in East African long rains during recent decades (Funk, Shukla et al., 2015; Nicholson, 2018). However, the magnitude of these trends remains relatively small and spatially variable.

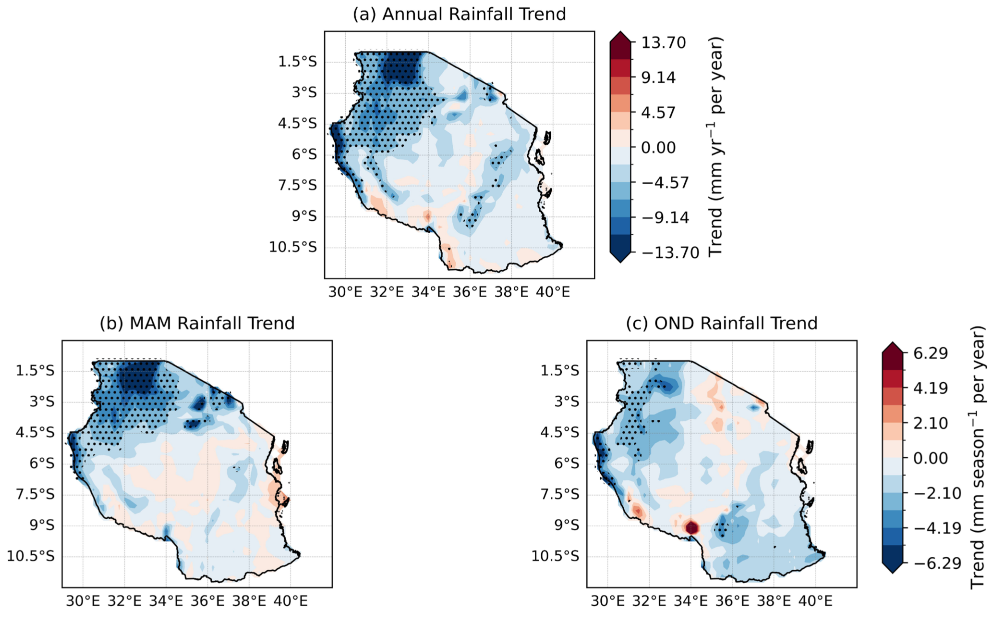

Figure 4. Spatial patterns of rainfall trends over Tanzania for 1979-2024: (a) Annual total, (b) MAM (March-May) total, and (c) OND (October-December) total.

The OND rainfall trend, on the other hand, exhibits a mixed pattern. Negative trends are observed over parts of western and central Tanzania, while small positive trends appear in the northeastern and southeastern regions. These patterns indicate that rainfall variability in Tanzania is dominated by inter-annual fluctuations rather than strong long-term trends, which is consistent with previous climatological studies in East Africa (Nicholson, 2018). Future studies should consider applying modified Mann-Kendall approaches or pre-whitening techniques to account for serial correlation and improve the robustness of significance testing.

3.3. Temporal Variations in Rainfall

The standardized rainfall anomaly time series (**Figure 5**) highlights pronounced inter-annual variability in rainfall over Tanzania during the study period. For annual rainfall, several years experienced above-normal rainfall conditions, including 1983, 1987, 1990, 1998, 2018, and 2023, where standardized anomalies exceeded +1. In contrast, strong negative anomalies occurred during 1993, 2003, and 2005, with anomaly values below −2, indicating severe drought conditions.

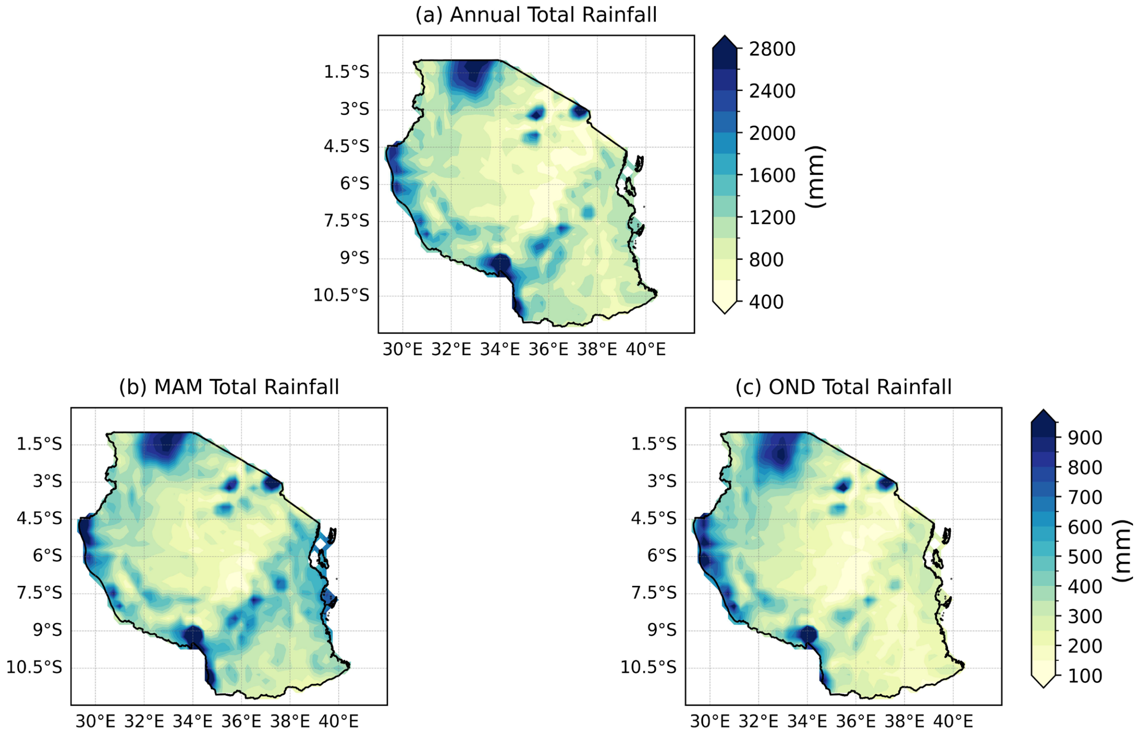

Figure 5. Spatial distribution of climatological total rainfall over Tanzania for 1979-2024: (a) Annual total, (b) MAM (March-May) total, and (c) OND (October-December) total.

Seasonally, the MAM rainfall anomalies show substantial variability, with wetter-than-normal conditions observed in 1980, 1988, 2018, and 2019, while dry conditions occurred in 1999, 2001, 2003, and 2021 as illustrated in **Figure 6**. These fluctuations are consistent with reported variability in the East African long rains, which are influenced by regional atmospheric circulation patterns and oceanic forcing.

The OND rainfall anomalies show even stronger inter-annual variability. Significant wet events occurred during 1982, 1986, 1997, 2006, and 2019, while drought conditions occurred during 1993, 1999, 2005, and 2016 (**Figure 6**). The extremely wet 1997-1998 event corresponds to a strong El Niño and positive Indian Ocean Dipole event, which is known to enhance rainfall over East Africa during the short rains season (Saji et al., 1999; Black et al., 2003).

Monthly rainfall anomalies further reveal variability across different months. For example, strong positive anomalies occur in March 1998, October 2019, and December 1997, while negative anomalies appear in January 1984, May 2003, and July 2010. These fluctuations highlight the influence of large-scale climate variability on monthly rainfall patterns.

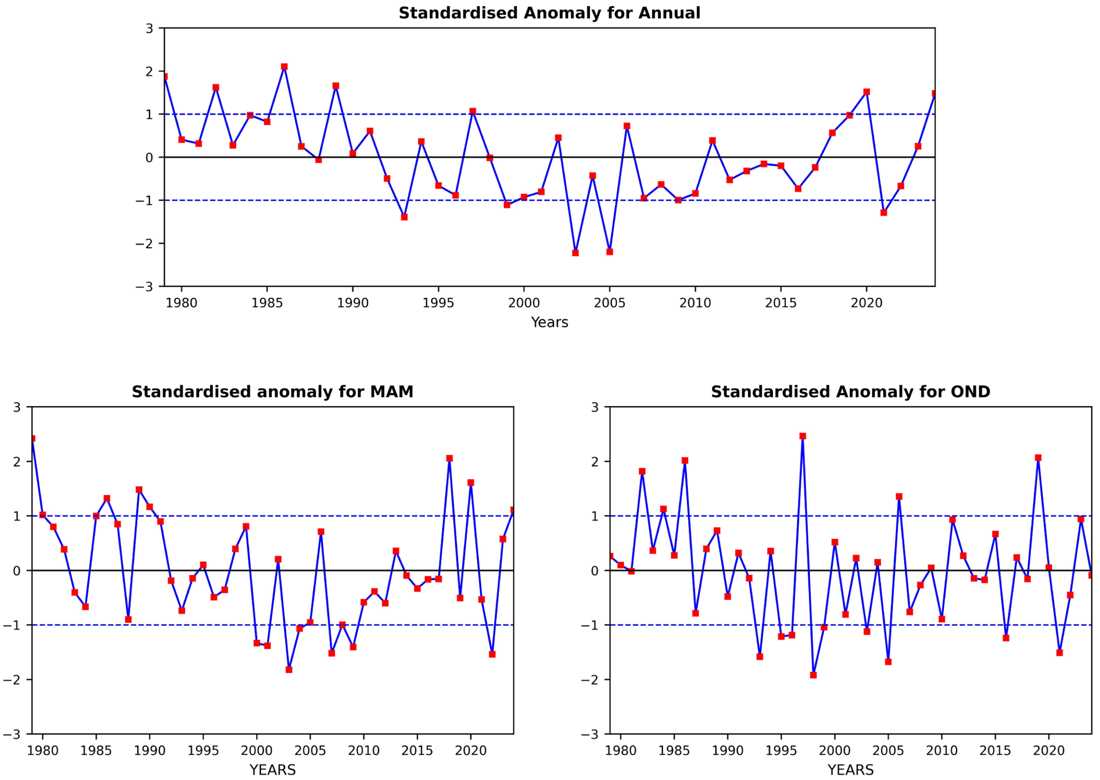

Figure 6. Inter annual variability of Tanzania area-mean rainfall expressed as standardized anomalies (z-scores) for the annual total (top), MAM (March-May; bottom left) and OND (October-December; bottom right) during 1979-2024.

3.4. Empirical Orthogonal Function (EOF) Analysis

The EOF analysis identifies the dominant spatial modes of rainfall variability over Tanzania. For the MAM season, the first EOF mode (EOF1) explains 42.5% of the total variance, indicating that a large portion of rainfall variability occurs coherently across much of the country. The spatial pattern of EOF1 shows broadly consistent rainfall variability across Tanzania, with stronger loadings in the northwestern and central regions. The second mode (EOF2) explains 14.0% of the variance and exhibits a clear north-south dipole pattern, indicating contrasting rainfall variability between northern and southern Tanzania (**Figure 7**). Such dipole structures are commonly associated with regional atmospheric circulation changes and local topographic influences (Hannachi et al., 2007). For the OND season, the dominant mode of variability is even stronger. The first EOF mode (EOF1) explains 69.1% of the total variance, suggesting that rainfall variability during the short rains season is largely controlled by a single dominant spatial pattern across Tanzania (**Figure 8**). The second mode (EOF2) explains 8.3% of the variance and highlights regional variability between the northwestern and southeastern regions. The corresponding principal component time series (PC1 and PC2) indicate significant inter-annual fluctuations, with strong peaks around 1997-1998, 2006, and 2019, which coincide with major ENSO and Indian Ocean Dipole events known to influence East African rainfall variability (Nicholson & Kim, 1997; Tierney et al., 2015).

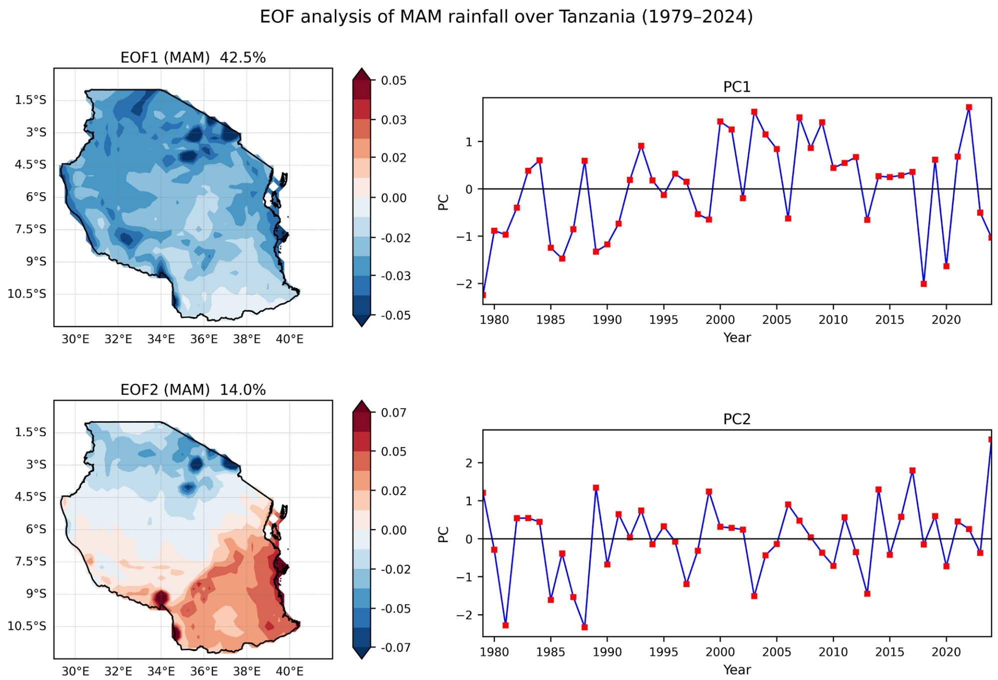

Figure 7. EOF analysis of MAM (March-May) rainfall over Tanzania (1979-2024), showing the leading spatial modes (EOF1-EOF2) and their associated standardized principal components (PC1-PC2).

3.5. Relationship between SSTs and Rainfall at Annual, MAM, and OND Seasons

The correlation analysis between Tanzania rainfall anomalies and global sea surface temperature anomalies (**Figure 9**) reveals important teleconnections between rainfall variability and large-scale oceanic processes.

At the annual scale, moderate correlations are observed between rainfall and SST anomalies in the tropical Pacific Ocean, suggesting the influence of the El Niño-Southern Oscillation (ENSO) on rainfall variability in Tanzania as illustrated in **Figure 10(a)**. Positive SST anomalies in the central and eastern Pacific are associated with enhanced rainfall in parts of East Africa (Nicholson & Kim, 1997). For the MAM season, correlations with global SST anomalies are relatively

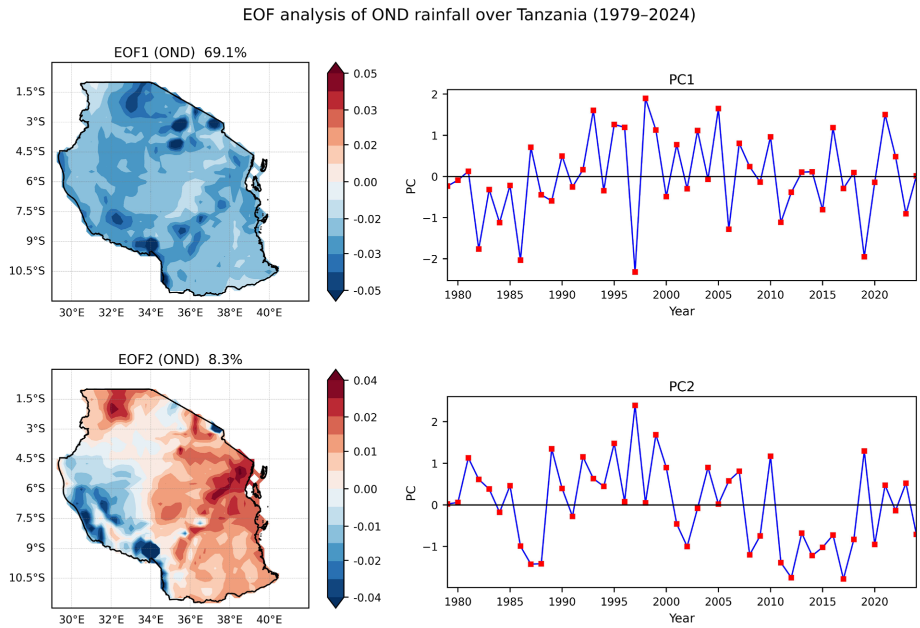

Figure 8. EOF analysis of OND (October-December) rainfall over Tanzania (1979-2024), showing the leading spatial modes (EOF1-EOF2) and their associated standardized principal components (PC1-PC2).

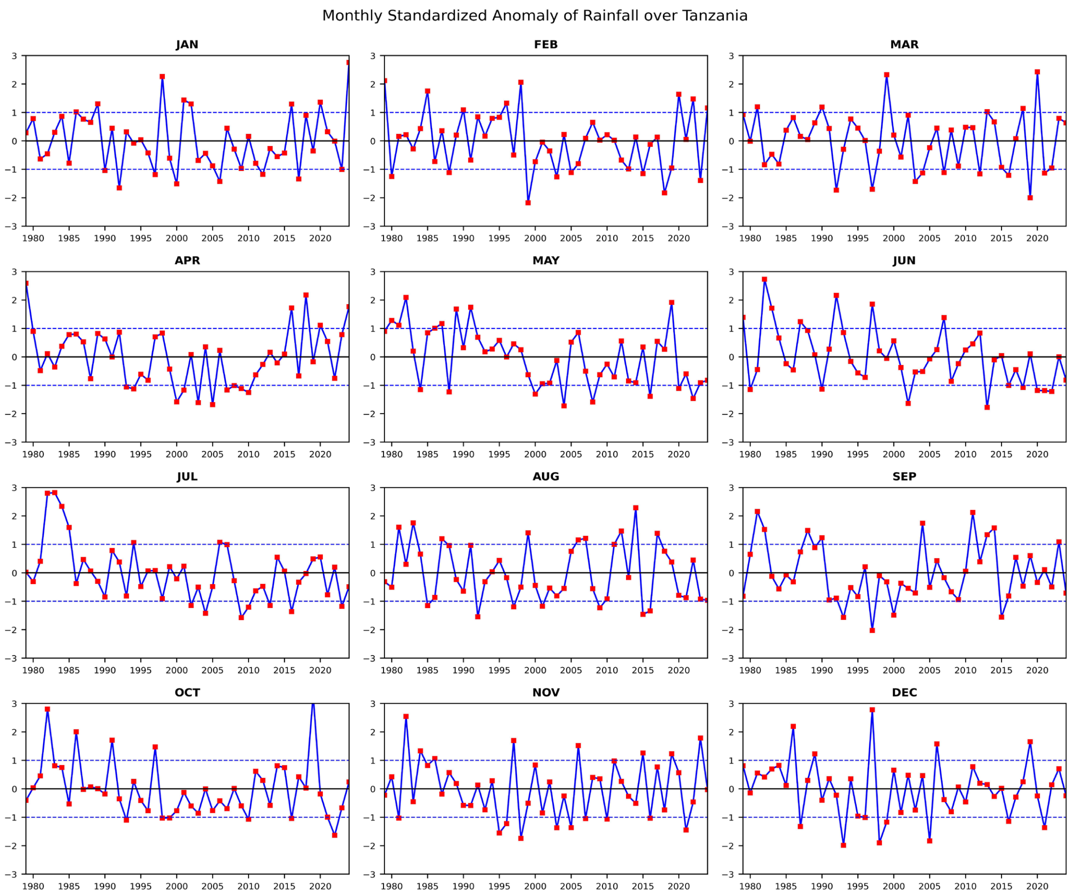

Figure 9. Monthly standardized rainfall anomalies (z-scores) for Tanzania for each calendar month (Jan-Dec) during 1979-2024, based on area-mean monthly totals masked to the Tanzania boundary.

weak, indicating that the long rains are influenced by more complex regional atmospheric processes rather than strong oceanic forcing as illustrated in **Figure 10(b)**. This finding is consistent with previous studies showing that the East African long rains have weaker links with ENSO compared with the short rains (Dunning et al., 2016; Nicholson, 2018).

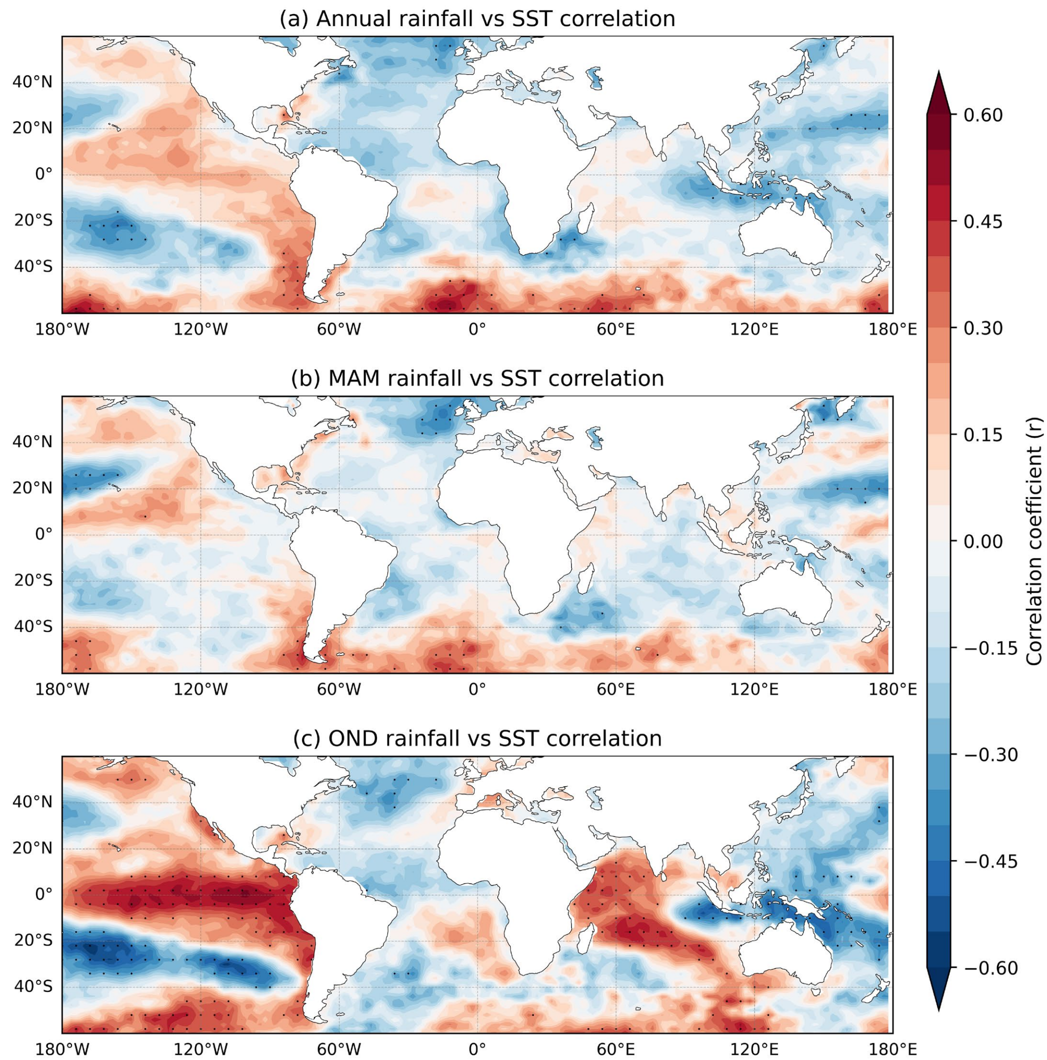

Figure 10. Spatial correlation between area-averaged rainfall anomalies over Tanzania and global sea surface temperature (SST) anomalies for (a) annual, (b) MAM (March-May), and (c) OND (October-December) during 1979-2024.

In contrast, the OND season exhibits strong correlations with SST anomalies in the western Indian Ocean and the tropical Pacific Ocean. Strong positive correlations appear in the western Indian Ocean, while negative correlations are evident in parts of the eastern Indian Ocean, reflecting the signature of the Indian Ocean Dipole as shown in **Figure 10(c)**. During positive IOD events, warm SST anomalies in the western Indian Ocean enhance convection and moisture transport toward East Africa, resulting in increased rainfall during the short rains season (Saji et al., 1999; Black et al., 2003). It is important to note that Tanzania exhibits both bimodal and unimodal rainfall regimes depending on geographic location (Nicholson et al., 2018). Therefore, national area-mean rainfall values presented in this study should be interpreted as generalized indicators of overall rainfall variability rather than representations of localized rainfall behavior. While the area-averaged approach is useful for capturing broad-scale climate variability and teleconnections, it may mask regional differences between northern bimodal regions and southern unimodal regions. Consequently, the spatial analyses presented alongside area-mean results are essential for understanding regional rainfall characteristics.

These results highlight the important role of ocean-atmosphere interactions in driving rainfall variability over Tanzania, particularly during the OND season when rainfall is strongly influenced by Indian Ocean SST variability.

4. Conclusion and Recommendations

This study investigated the spatial and temporal variability of rainfall over Tanzania during the period 1979-2024 and examined its relationship with global sea surface temperature (SST) anomalies using reanalysis datasets and statistical techniques including standardized anomalies, the Mann-Kendall trend test, Empirical Orthogonal Function (EOF) analysis, and correlation analysis.

The spatial analysis revealed strong regional contrasts in rainfall distribution across Tanzania. The Lake Victoria basin and coastal regions receive the highest rainfall amounts, with annual totals exceeding 2400 mm, while the central plateau experiences considerably lower rainfall, typically below 800 mm. Seasonal analysis confirmed the presence of bimodal rainfall patterns in northern and eastern Tanzania, characterized by the long rains (MAM) and short rains (OND), while southern regions exhibit a unimodal rainfall regime. Trend analysis using the Mann-Kendall test and Sen's slope estimator indicated generally weak and spatially heterogeneous rainfall trends across Tanzania, with slight decreasing tendencies observed in parts of the northwestern region and limited positive trends in some southern areas.

Temporal analysis showed pronounced inter-annual rainfall variability, with notable wet years such as 1983, 1998, 2018, and 2023, and drought conditions occurring in 1993, 2003, and 2005. The EOF analysis identified dominant spatial modes of rainfall variability, with the first EOF mode explaining 42.5% of variance during MAM and 69.1% during OND, indicating stronger spatial coherence in short-rains variability. Correlation analysis further revealed significant teleconnections between Tanzania rainfall and global SST anomalies, particularly during the OND season, when rainfall variability is strongly associated with Indian Ocean Dipole and ENSO-related SST patterns. Future research should therefore focused on the unimodal season rainfall trends and variability. These findings highlight the importance of ocean-atmosphere interactions in controlling rainfall variability in Tanzania, providing useful insights for improving seasonal climate prediction and climate risk management in the region.

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Conflicts of Interest

The authors declare that there is no conflict of interest regarding the publication of this paper.

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