# Investigation of Temporal Trends and Spatial Patterns of Extreme Temperatures and Their Relationship to Climate Circulation Indices in Tanzania

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### Abstract

This paper examined the spatial and temporal patterns of selected temperature extreme indices using the Mann-Kendall method (MK), the standard t-test, and the Pearson correlation analysis method. The relationship between extreme temperature events and climate circulation indices was analysed in Tanzania between 1983 and 2016 using data from 1961 to 2018. The results uncover a rise in the frequency and intensity of balmy days and nights across Tanzania. It suggests a significant increase in trends and the frequency of mild temperature index days and warm nights. It also indicates an increase in the trends for warm temperature indices (hottest days (TXx), coldest days (TNx), warm days (TX90p), tropical night (TR20), and Warm Spell Duration Indicator (WSDI); and a decrease in cold temperature indices (cold days (TX10p), cold nights (TN10p), cold days (TXn), and Cold Spell Duration Indicator (CSDI); which imply that the lower temperature was gradually decreasing more than in the past. The results further suggest that warm days and nights are significantly correlated with the Tropical Northern Atlantic Index (TNA), the Interdecadal Pacific Oscillation (IPO), the Atlantic Multidecadal Oscillation (AMO), and the El Nino-Southern Oscillation (ENSO). The circulation indices, which were found to be substantially associated with temperature extreme indices, can aid in forecasting, and may potentially serve as a foundation for future studies, particularly in the dynamics and physical mechanisms related to temperature extremes. The results presented in this paper are also vital for developing proper mitigation and adaptation measures to reduce future risks associated with extremely high-temperature events.

**Keywords:** spatio-temporal analysis, extreme temperatures, circulation indices, trend analysis, Tanzania.

### 1. Introduction

The earth's surface has been steadily warming over the course of the last three decades, particularly from 1983 to 2012, which were the warmest years; and have varied considerably over most parts of the globe with observable regional variations (Ires, 2021; Sun et al., 2023). Tanzania, like other regions, is also characterised by a variety of extreme temperature events with high frequency and seasonality, which encompass a wide range of impacts, such as droughts and floods that have occurred frequently over the past few decades (Mdemu,

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2021 & Luhunga and Songoro, 2020). According to several studies (e.g., Dawley et al., 2019; Msemo et al., 2021), these hydrological extreme events are directly correlated with climate extreme events. Additionally, a study by Kavishe and Limbu (2020) revealed that temperature, which varies from region to region, has a close relationship with precipitation. Several studies (e.g., Trajkovic et al., 2016; Andersen et al., 2022; Anghel et al., 2023; Cai et al., 2023) have demonstrated that alterations in temperature patterns, specifically increases in extreme temperatures, can have negative effects on vegetation. Higher temperatures can cause drought stress, increased evaporation, changes in rainfall patterns, and more frequent heatwaves: all of which are detrimental to plant growth and ecosystem functioning.

Several studies (e.g., Chang'a et al., 2017; Luhunga, 2022) have investigated the spatial and temporal pattern of extreme temperatures in Tanzania. In their findings, it was reported that the recent change in temperature extremes has been consistent with global warming. Chang'a et al. (2017) found that extreme climate events have increased in frequency and intensity since the mid-20th century, mostly over northern Tanzania. On the other hand, the cause of temperature extremes in Tanzania has not been thoroughly investigated, despite several atmospheric circulation alterations, including El Nino-Southern Oscillation (ENSO), Indian Ocean Dipole (IOD), Atlantic Multidecadal Oscillation (AMO), Pacific Decadal Oscillation (PDO), Interdecadal Pacific Oscillation (IPO), Tropical Northern Atlantic Index (TNA), and Pacific North American Oscillation (PNA) (Limbu & Guirong, 2020; Makula et al., 2020). A number of studies (e.g., Mademu, 2021; Bile & Limbu, 2022) have linked these alterations to El Nino and La Nina events.

The 5<sup>th</sup> IPCC Assessment report indicates that extreme temperature affects various economic sectors, such as agriculture and water; but the extent of these extreme temperature trends in developing countries like Tanzania are still unknown (IPCC, 2014). Changes in temperature extremes could significantly affect the condition of local natural water resources by hydrological cycle elements such as evapotranspiration, precipitation, runoff, etc. (Wang et al., 2015; Grant, 2017; Ghorbani et al., 2018; Liu et al., 2018). To comprehend the spatial and temporal patterns of extreme temperature events is crucial: it serves as a prerequisite and vital input for devising and implementing effective strategies to buffer and adapt to the impacts of climate change (Liu & Xu, 2020).

Most of the previous studies (e.g., Luhunga & Songoro, 2020; Chang'a et al., 2017) present the impacts of climate change by focusing on specific regions of Tanzania, or short time periods. Little is known about the long-term temporal trends and spatial patterns of extreme temperatures across the entirety of Tanzania and their relationship with various climate circulation indices. Also, most of the work done before has mostly relied on observational data without

using advanced statistical methods; or a wide range of climate circulation indices to figure out what might be causing the trends that have been seen. Addressing these research gaps is crucial for a more holistic understanding of the complex interactions between extreme temperatures, climate circulation patterns, and their implications for Tanzania's climate resilience strategies and adaptation measures. Therefore, to fill these research gaps, this paper examines the temporal trends and spatial patterns of extreme temperatures, and their relationship to climate circulation indices over Tanzania.

### 2. Context and Methods

### 2.1. Description of the Study Area

Tanzania is a country located in eastern Africa between longitudes  $28^{\circ}$  E and  $42^{\circ}$  E, and latitudes  $0^{\circ}$  and  $12^{\circ}$  S. The elevation of the country is 0–5895m above the mean sea level. The country is surrounded by big lakes such as Lake Victoria, Lake Tanganyika, and Lake Nyasa; and the Indian Ocean in the eastern part of the country (Kijazi & Reason, 2009a). It has a varying topography, with the highest mountain in Africa, Mount Kilimanjaro, at a height of 5895m above sea level (Kijazi & Reason, 2009b). The climatological average temperature ranges between  $27^{\circ}$ C and  $29^{\circ}$ C along the coast and in the offshore islands of Tanzania; while in the central, northern, and western parts, temperatures range between  $20^{\circ}$ C and  $30^{\circ}$ C (Chang'a et al., 2017; World Bank Group, 2021).

### 2.2. Sources of Data

This study used daily maximum temperature (TX) and minimum temperature (TN) to assess changes in the frequency and intensity of extreme temperatures in Tanzania. Both maximum and minimum temperature satellite data were accessed from the Climate Hazards Centre (CHC) at a high resolution of  $0.05^{\circ} \times 0.05^{\circ}$ , approximately 5km, referred to as CHIRTS-daily; spanning from 1983 to 2016. The available daily maximum and minimum temperatures were used to study extreme temperature indices as recommended by the Expert Team on Climate Change Detection and Indices (ETCCDI). This dataset has been widely used in previous climate-related studies (i.e., Pan et al., 2019; Iyakaremye et al., 2021a); and has successfully proved to represent regional climate characteristics. Further details about the temperature datasets employed in this paper can be found at https://www.chc.ucsb.edu/data/chirtsdaily.

Moreover, some teleconnection patterns such as El Niño-Southern Oscillation (ENSO), Indian Ocean Dipole (IOD), Atlantic Multidecadal Oscillation (AMO), Pacific Decadal Oscillation (PDO), Interdecadal Pacific Oscillation (IPO), Tropical Northern Atlantic Index (TNA), and Pacific North American Oscillation (PNA) were considered to investigate the possible relationship between large-scale atmospheric oscillation indices and temperature extremes over the study area. The relationships between the large-scale atmospheric oscillation indices and temperature between the large-scale atmospheric oscillation indices and temperature extremes were calculated during both the OND and MAM rainy seasons.

#### 2.3. Data Analysis

This paper examined thirteen (13) core temperature indices in the study regions, namely hottest days (TXx); coldest days (TNn), TXn, TNx; warm days (TX90p), warm nights (TN90p); Warm Spell Duration Indicator (WSDI); summer days (SU30); cold days (TX10p); cold nights (TN10p), tropical nights (TR20), Cold Spell Duration Indicator (CSDI), and daily temperature range (DTR). The chosen extreme climate indices include both absolute value-based and percentile. To detect extreme temperature change, the indices used were the ones that contain variations caused by climate processes only. The dataset used to construct these indices was homogenous (i.e., free of non-climate-related variation) through a bootstrap resampling procedure to estimate exceedance frequencies during the base period. A detailed procedure for the calculation of those indices can be found at http://etccdi.pacificclimate.org/list 27 indices.shtml, and in a study done by Zhang et al. (2005). The extreme temperature indices provide an overview of temperature statistics, particularly on extreme aspects, and help to compare regional and global extreme temperature change in a standardised way (Wang et al., 2017; Umutoni & Limbu, 2023). Table 1 presents a detailed description of these thirteen (13) indices. The indices listed in Table 1 were calculated annually between 1983 and 2016.

Tab	le :	1: 1	Sel	lected	Tem	perature	Extreme	Indices
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No	Index	Definition	Unit
1	SU30 (summer days)	Annual count when TX (daily maximum) > 30 °C	Days
2	TR20 (tropical nights)	Annual count when TN (daily minimum) > 20 °C	Days
3	TXx (warmest days)	Monthly maximum value of daily maximum temperature	°C
4	TXn	Monthly minimum value of daily maximum temperature	°C
5	TNx	Monthly maximum value of daily minimum temperature	°C
6	TNn (coldest days)	Monthly minimum value of daily minimum temperature	°C
7	TN10p (cold nights)	Percentage of days when TN < 10th percentile	Days
8	TX10p (cold days)	Percentage of days when TX < 10th percentile	Days
9	TN90p (warm nights)	Percentage of days when TN > 90th percentile	Days
10	TX90p (warm days)	Percentage of days when $TX > 90$ th percentile	Days
11	WSDI (Warm spell	Annual count of days with at least 6	°C
	duration index)	consecutive days when TX>90 <sup>th</sup> percentile	
12	CSDI (Cold spell	Annual count of days with at least 6	°C
	duration index)	consecutive days when $TN < 10$ th percentile	
13	DTR (Daily temp.	Monthly mean difference between TX and TN	°C
	range)	-	

The extreme indices considered in this paper were calculated using the RClimDex 1.1 software (http://etccdi.pacificclimate.org/software.shtml) on a daily basis for the study period. A quality control (QC) of the data was performed to identify gross errors through checks, tolerance tests, internal consistency, temporal coherence, and spatial coherence before running the RClimDex software. After the QC check, the data series were uploaded and the directory was set; followed by loading the data, setting the parameters and

downloading the series, executing the QC; and finally, the log folder was used to identify the preferential extreme temperature indices. The RClimDex has been widely used to study the temporal and spatial distribution and variability of temperature extremes in different regions of the world (Guan et al., 2015; Jiang et al., 2016; Sun et al., 2017; Mehmood et al., 2022).

This paper employed the regression technique based on iteratively reweighted least squares to investigate the trends in extreme high-temperature events over the study domain. This method has the advantage of resisting outliers; and has been widely used in recent studies (i.e., Kishore et al., 2016; Basha et al., 2017; Iyakaremye et al., 2021b; Iyakaremye et al., 2022). The Student's ttest was used to test the significance of the linear trend at a 95% confidence level using the GrADS software. In addition, the Pearson correlation was also utilised to investigate the possible relationship between the large-scale atmospheric oscillation indices and extreme temperature events over the study region using a Python software. Furthermore, the probability density function was used to examine if the break-point of the temperature properties for the sub-periods 1983–1999 and 2000–2016 are different by using a Python software. The sub-periods were chosen based on recent research findings that documented changes in the regional climate in the late 1990s (Limbu & Tan, 2019; Makula & Zhou, 2021; Iyakaremye et al., 2022).

### 3. Results and Discussion

### 3.1. Temporal Changes in Extreme Climatic Indices

Figure 1 shows the temporal variations in average annual temperature extremes in Tanzania for the period from 1983 to 2016. As can be observed, the hot indices TN90p and TX90p increased at the rates of 0.343 and 0.292 day/year, respectively; but also the TNx and TXx indices increased at the rates of 0.009 and 0.014°C/year, respectively, during 1983–2016 (Figure 1c, d, g, and h). The increasing trends for TN90p and TX90p are significant at a 95% confidence level; while the trend for TNx and TXx are insignificant at a 95% confidence level. However, the cool indices, TN10p and TX10p, exhibited a significant decline trend at the rates of -0.2353 and -0.2709 day/year, respectively, for the same period (Figure 1a, b); while TNn and TXn displayed insignificant increasing trends of 0.006 and 0.003°C/year, respectively (Figure 1e and f). Moreover, other indices like SU30 and DTR exhibited insignificant increasing trends at 1.289 and 0.007 days/year; and TR20 and WSDI (CSDI) displayed nonsignificant increasing (decreasing) rates at 0.478 and 0.084 days/year (-0.198 days/year) during the study period.

The results show that the frequency of both warm nights and days has shown increasing trends over the study area. Similarly, the intensity of warm days and nights has also increased in recent decades. Moreover, it was also found that most parts of the country experienced significantly increasing trends in the frequency of warm days and an increase in the number of warm nights across Tanzania.



Figure 1: The temporal distribution of the annual mean of temperature extreme indices over the study area during the period 1983–2016.

The rising number of warm days and nights revealed in this paper agrees with the previous studies by Omondi et al. (2014) and Gebrechorkos et al. (2019) over East Africa; and Iyakaremye et al. (2022) in their study over Africa. Similar results were also revealed by Hu and Huang (2020) in their study done over Western Sahara and some parts of Northern Africa from 1979 to 2012 during the summer season. The intensified and frequent warm days and nights could affect human health since consecutive hot days and hot nights might lead to human beings failing to fully recuperate at night. In recent decades, East Africa has experienced more drought events, coinciding with the increasing trend of temperature extremes; for example, in 2010–2011, Ethiopia, Uganda, Somalia, and Kenya experienced a severe drought event that severely affected about 10m people (Nicholson, 2014).

### 3.2. Spatial Changes in Extreme Climatic Indices

The spatial patterns of variation in the annual mean of extreme temperature indices are displayed in Figures 2, 3, 4, and 5. The changes in the TNn, TNx, TXn, and TXx depicted significant upward trends in southern and eastern Tanzania, while the western and central regions of the country showed a significant downward trend (Figure 2).





Note: The hatched star indicates the significant region at confidence level of 95%.

The changes in TN10p showed a significant downward trend in the south, east, and north of the study domain, with a significant upward trend in the western regions of Tanzania (Figure 3a). Conversely, TN90p displayed a significant upward trend in the south, east, and north of the study area, with a significant

downward trend in the western regions of Tanzania (Figure 3b). TX10p showed significant declining trends over most of the country, except the western parts of the country (Figure 3c). For the hot extreme, TX90p showed significant rising trends throughout the country (Figure 3d).



Figure 3: Spatial distributions of extreme temperature indices for (a) TN10p (b) TN90p (c) TX10p (d) TX90p during the period 1983–2016.

Note: The hatched star indicates the significant region at confidence level of 95%.

As can be seen in Figure 4, the CSDI (TR20) revealed a decreasing (increasing) trend over most parts of the study region, except the western and central areas of Tanzania, which exhibited an increasing (decreasing) trend. On the other hand, the WSDI, DTR, and SU30 (Figure 4b, c, and e) showed significant rising trends over most areas of the country.



Temporal Trends and Spatial Patterns of Extreme Temperatures

Figure 4: Spatial distributions of extreme temperature indices for (a) CSDI (b) WSDI (c) DTR (d) TR20 (e) SU30 during the period 1983–2016. Note: The hatched star indicates the significant region at confidence level of 95%.

Generally, the hot extremes were observed to rise and the cool extremes to decline in most regions of Tanzania, indicating that hot days and nights are increasing, and cold days and nights are decreasing. In Tanzania, drought conditions are observed more frequently in the northern and central portions (Arusha, Manyara, Shinyanga, Simiyu, and Dodoma) (Osima, 2014; World Bank, 2020). For instance, a drought that hit the Longido district in 2008/09 resulted in severe food insecurity and a significant loss of livestock (Bowen et al., 2010). Southern Tanzania experienced a severe drought event during the December-February (DJF) rainy season, while northern Tanzania experienced a severe drought during the March-June (MAMJ) rainy season for the period from 1999 to 2014 (Harrison et al., 2019).

### 3.3. Probability Density Functions of Extreme Climatic Indices

Figure 5 presents the annual probability density functions (PDFs) of extreme temperature indices over Tanzania in two different sub-periods of 1983–1999 and 2000–2016. The PDFs of TNn showed almost the same mean with the change of peak values of density from 0.5 to 0.8 (Figure 5a). On the other hand, TNx experienced a rightward shift with the change in the highest value in PDFs from 1 to 1.2 (Figure 5b). Figure 5c exhibited a leftward shift of the PDFs of TXn, with the peak values changing from 1.3 to 0.9. The PDFs of TXx showed a slight change in peak values from 0.6 to 0.8, with a rightward shift of skewness (Figure 5d). The PDFs of TN10p and TX90p showed a leftward shift, from 0.04 and 0.1 during 1983–1999 to 0.08 and 0.06 during 2000–2016 (Figures 5e and h). The PDFs of TN90p and TX10p exhibited almost the mean during the two subperiods, with the change in peak values from 0.07 and 0.06 to 0.06 and 0.14, respectively (Figures 5f and g). The DTR, TR20, and SU30 PDFs displayed a leftward shift between the two periods, with a change in peak values from 2.1, 0.024, and 0.19 to 1.9, 0.022, and 0.012, respectively (Figures 5k, l, and m).

The modulations observed in the distribution patterns of extreme temperature indices indicate a transition in the direction of a warmer situation in Tanzania that coincides with the findings of trends in extreme temperature indices presented earlier in this paper.

### 3.4. Relationship between Extreme Temperature Indices and Oceanic Circulation Indices

This paper also analysed the relationship among the extreme temperature indices, as presented in Figure 6. As can be observed, a significant relationship among the extreme temperature indices is revealed (p<0.01). Most cool extremes and hot extremes are significantly negatively correlated (p<0.01). Moreover, the hot and cool extremes were significantly positively related to each other (p < 0.01). For example, the hot days displayed a positive relationship with hot extremes, and showed a negative relationship with cool extremes.



Figure 5: Annual probability density function of extreme climate indices for the sub-periods 1983-1999 (blue line) and 2000-2016 (red line).



Paul T.S. Limbu & Exavery K. Makula

Figure 6: Pearson's correlation between annual extreme temperature indices

Furthermore, this paper investigated the relationship between extreme temperature indices and large-scale atmospheric and oceanic oscillations during MAM seasons, as shown in Figure 7. It is revealed that TN10p is significantly negatively correlated with IPO (p<0.05), PDO (p<0.01), and ENSO (p<0.05). The TN90p showed a significant positive correlation with TNA, IPO (p<0.01), PDO (p<0.01), AMO (p<0.05), and ENSO (p<0.01). TNn exhibited a significant positive relationship with PNA (p<0.05), while TNx is significantly positively correlated with TNA (p<0.05), IPO (p<0.01), and ENSO (p<0.05). Moreover, TX10p exhibited a significant negative correlation with PNA (p<0.05). Moreover, TX10p exhibited a significant negative correlation with PNA (p<0.01), TNA (p<0.05), IPO (p<0.01), PDO (p<0.05), and ENSO (p<0.01); while TX90p exhibited a significant positive relationship with TNA, IPO (p<0.01); while TX90p exhibited a significant positive relationship with TNA, IPO (p<0.01); while TX90p exhibited a significant positive relationship with TNA, IPO, AMO, and ENSO at a 5% significance level.



Figure 7: Pearson's correlation coefficients between seasonal mean (MAM) extreme temperature and atmospheric oscillation indices in Tanzania: 1983–2016.

Note: \*significant at the 0.05 level; \*\*significant at the 0.01 level).

The associations of the extreme temperature indices with the large-scale atmospheric and oceanic circulation indices during the OND season were also examined, as presented in Figure 8. The DTR displayed a significant negative association with IPO (p<0.05), ENSO (p<0.01), and DMI (p<0.01). TN10p exhibited a significant negative correlation with TNA (p<0.01), AMO (p<0.05), ENSO (p<0.05), and DMI (p<0.05); whereas TN90p depicted a significant positive relationship with TNA (p<0.01), IPO (p<0.05), AMO (p<0.05), ENSO (p<0.01), and DMI (p<0.05). TNn showed a significant positive association with IPO (p<0.05), ENSO (p<0.01), and DMI (p<0.05). Furthermore, TX10p showed a significant negative correlation with TNA (p<0.01) and AMO (p<0.01). Moreover, TXn showed a significant negative correlation with TNA (p<0.01) and AMO (p<0.05), while TXx displayed a significant positive relationship with TNA (p<0.05).

Significant relationships between temperature extremes and large-scale atmospheric and oceanic oscillations were also observed, such as warm days

being significantly correlated with TNA, IPO, AMO, and ENSO. The large-scale oscillations revealed in this paper to be significantly linked to extreme temperature indices can help in updating temperature forecasts over the region. Previous studies over different regions have shown the linkage of large-scale oscillations with extreme temperature indices. For instance, Wang et al. (2018) reported that temperature variations over Northern Eurasia result from ENSO, which disturbs the air temperature in winter in Northern China. Moreover, Mallick et al. (2022) observed that the extreme temperature indices over Bangladesh were negatively correlated with the Southern Oscillation Index (SOI), Indian Ocean Dipole (IOD), and the North Atlantic Oscillation (NAO).

Ш	-0.58**	-0.35*	0.43	0.47**	0.42*	0.27	-0.2	-0.35*	-0.16		- 0.8
ENSO	-0.52**	-0.41	0.5**	0.53**	0.48**	0.25	-0.28	-0.19	-0.32		- 0.6
АМО	0.27	-0.41	0.39	0.13	0.28	-0.53**	0.56**	0.19	0.23		- 0.4
PDO	-0.21	-0.22	0.22	0.41	0.17	0.18	-0.09	-0.097	-0.16		- 0.2
D9	-0.48**	-0.29	0.37*	0.48**	0.38*	0.28	-0.33	-0.2	-0.32		0.2
TNA	0.19	-0.44**	0.48**	0.18	0.37*	-0.43*	0.57**	0.076	0.34*		- 0.4
PNA	0.017	-0.13	0.099	0.26	-0.011	-0.065	0.16	0.12	-0.066		0.6
	DTR	TN10P	TN90P	TNn	TNx	TX10P	TX90P	TXn	TXx		0.8

Figure 8: Pearson's correlation coefficients between seasonal mean (OND) extreme temperature and atmospheric oscillation indices in Tanzania: 1983–2016.

Note: \*significant at the 0.05 level; \*\*significant at the 0.01 level).

### 5. Conclusion and Recommendations

This paper investigated the spatial and temporal trends of extreme temperature indices in Tanzania during 1983–2016, and their possible associated large-scale atmospheric and oceanic oscillations. High-resolution gridded maximum and minimum surface temperature datasets from the CHC archive were utilised in this paper. The paper has revealed an increasing number of warm days and an intensified magnitude of warm days and nights over Tanzania. Moreover,

significant increasing trends in the frequency of both warm days and nights were observed over most parts of the study area. Generally, the results revealed that the trends for the warm temperature indices (TXx, TNx, TX90p, TN90p, TR20, SU30, and WSDI) were increasing, while the cold temperature indices (TX10p, TN10p, TXn, and CSDI) were decreasing (i.e., the lower temperature was gradually decreasing more than in the past).

This paper has revealed significant relationships between temperature extremes and large-scale atmospheric and oceanic indices. For instance, warm days correlate significantly with TNA, IPO, AMO, and ENSO. Likewise, warm nights are considerably associated with TNA, IPO, PDO, AMO, and ENSO. The circulation indices identified in this paper to be significantly associated with temperature extreme indices can aid in weather forecasting and providing the basis for future studies to better understand the dynamics and physical mechanisms allied with temperature extremes. However, extreme temperature events are affected by many factors, such as anthropogenic activities, sea surface temperatures, and local fluxes: all of which are considered non-linear dynamics and non-stationary processes, particularly in arid regions with various landforms and topographies (Pi et al., 2020). Therefore, further detailed research investigating the influence of different external drivers on extreme high-temperature events over the study region will highly add value to the existing literature. Furthermore, the findings presented herein are vital for developing proper mitigation and adaptation measures to reduce future risks associated with extremely high-temperature events.

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