Spatiotemporal Rainfall Variability in the Borena Zone, Southern Ethiopia, and Its Linkage to Large-Scale Climate Oscillations: Implications for Food Security Among Pastoral Households

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Abstract

This study focuses on daily extreme climate indices and their underlying causes, rather than traditional average climate investigations. The primary aim is to effectively strategize adaptation measures for climate extremes and ensure food security. The research was conducted in the Borena Zone, an area that has experienced recurrent extreme weather events, particularly droughts, over the past few decades. Utilizing daily rainfall and temperature data sourced from the National Meteorological Agency (NMA) spanning from 1981 to 2020, the study examines the variability of climate extreme indices within the Borena Zone. In addition to mean maximum and mean minimum temperatures, six extreme temperature indices and five extreme rainfall indices were employed for a comprehensive analysis. The results from temporal analysis indicate that maximum daily maximum temperature (TXx), maximum daily minimum temperature (TNx), minimum daily maximum temperature (TXn), and maximum daily minimum temperature (TNn) exhibit significantly increasing trends ranging from 0.016 to 0.053°C/year. Conversely, the extreme temperature indices for cool days (TX10) and cool nights (TN10p) show decreasing trends ranging from 0.058 to 0.406%/year. The spatial analysis of extreme indices also reveals an overall increase in temperature across the zone, confirming a higher warming trend in the area. Among the extreme rainfall indices, the total precipitation (PRCPTOT) shows a very significant increasing trend ($p = 0.006$) of 3.65 mm/year. The number of very heavy rainfall days (R20mm) and the number of very wet days (R95p) also exhibit significant increasing trends, ranging from 0.05 to 2.044 mm/year. Conversely, continuous wet

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days (CWD) show a decreasing trend, while continuous dry days (CDD) demonstrate an increasing trend. The spatial analysis of rainfall indices corroborates the findings from the temporal analysis. Correlation analysis of daily rainfall with global indices such as Sea Surface Temperature (SST) and Sea Level Pressure (SLP) reveals a significant positive correlation with consecutive dry days (CDD) and a negative correlation with consecutive wet days (CWD). The results of this study indicate warming trends in the area, accompanied by erratic rainfall patterns that significantly affect evaporation rates and various key sectors, notably rainfed agriculture, leading to increased drought conditions.

Keywords: Climate indices, extremes, drought, temporal, spatial, Borena, Ethiopia

1. Introduction

Since the onset of the Industrial Revolution, climate extremes have increasingly affected various regions globally (McMichael, 2017). The impacts of global warming and other anthropogenic climate extremes have varied, causing significant harm to both the environment and human well-being (Shivanna, 2022). Tropical regions are particularly vulnerable due to their geographic location and limited technological advancements to mitigate hydro-meteorological hazards (Sahani et al., 2019). Developing countries like Ethiopia have seen a marked increase in climate risk, driven by exceptional weather events and low adaptive capacity (World Bank, 2021). Due to its heavy reliance on rain-fed agriculture and natural resources, Ethiopia is among the nation’s most sensitive to climatic variability and change. Future projections indicate that hydro-meteorological hazards and temperature extremes will become more frequent and intense (Beyene et al., 2022; Adem & Amsalu, 2021; Damtew et al., 2022; Dendir & Birhanu, 2022). Rising temperatures, both currently and in the future, are attributed to excessive greenhouse gas emissions from various sources. For instance, the global average surface temperature is projected to rise by 2.6 to 4.8°C by the end of the 21st century, following an increase of 0.3 to 0.6°C during the 20th century (IPCC, 2007). Extreme weather and climate events negatively impact livelihoods and contribute to the overall decline of ecosystems. The most significant shifts in surface temperature are expected to occur in Africa (IPCC, 2013).

The sub-Saharan region has seen a significant increase in heat wave occurrences in recent years, with studies indicating a rise in frequency and intensity due to climate change (Lelieveld et al., 2022). These heat waves have profound impacts on the environment and public health, exacerbating existing vulnerabilities in the region. Increases in surface temperature can disrupt the hydrological cycle, affecting critical processes such as evapotranspiration and precipitation patterns. Recent literature highlights that climate change is leading to altered rainfall distributions and increased evaporation rates, which in turn affect water availability and agricultural productivity (Zhou et al., 2023; IPCC, 2023). This disruption poses significant challenges for food security and sustainable development in the region.

The hydro-meteorological risks in the Horn of Africa are closely linked to the El Niño Southern Oscillation (Liebmann et al., 2014; Nicholson, 2017). Extreme climate events such as droughts and floods lead to severe consequences, including landslides, erosion, and reduced agricultural yields and water resources. Ethiopia's most crucial economic systems are increasingly vulnerable to climate variability and extreme occurrences, such as large floods and droughts, which severely impact people's lives, property, and natural resources (Adger et al., 2018). Significant portions of the nation, particularly the semi-arid and desert regions, are prone to high levels of climatic fluctuation and periodic droughts. Recent data indicate that the Borena Zone is one of the most drought-prone areas in Ethiopia (Ambelu et al., 2017; Bogale and Erena, 2022).

When assessing the variation and trends of temperature and rainfall extremes, it is essential to understand the relationships between rainfall variation and global-scale climate indices (Sillmann et al., 2017), which are key drivers of regional climate variability. For example, the development of global climate indices can trigger atmospheric-oceanic anomalies in the tropical Pacific, affecting climate parameters worldwide, particularly rainfall patterns (Unal et al., 2012). In Ethiopia, rainfall variations are primarily influenced by the seasonal migration of the Intertropical Convergence Zone (ITCZ) and the global climate system (Camberlin, 2009; Fazzini et al., 2015; Gleixner et al., 2017; Korecha and Barnston, 2007). While previous studies (e.g., Alhamshry et al., 2020; Diro et al., 2011; Segele et al., 2009) have reported associations between SST and Ethiopian rainfall, they often had limited temporal coverage and did not focus on the rainfall extremes in southern Ethiopia.

To address this gap, this study aims to investigate the association of various global climate indices with the variation of daily extreme rainfall indices in the Borena Zone, which is located in southern Ethiopia and frequently experiences extreme events and prolonged drought. In climate research, several studies have predominantly used annual and monthly mean average data, which can obscure significant variables that characterize extreme indices responsible for extreme events (Zhang et al., 2019).

Therefore, extreme indices derived from daily climate data aim to provide unbiased insights from weather observations, enhancing our understanding of extremes that significantly impact various ecosystems. Unlike previous studies, this research offers new insights into the trends of daily extreme temperature and rainfall indices for the study area, utilizing an extensive climate dataset from 1981 to 2020. Accordingly, the main objective of this study is to evaluate recent changes in the temporal variation and trends of daily temperature and rainfall extremes, as well as the impacts of extreme climate change in the area. Additionally, it explores the teleconnections between local rainfall and global indices. The results could provide essential scientific information on historical climate change, which is valuable for the management of water resources and hydrological systems in the region.

2. Materials and Methods

2.1. Theoretical Framework

The study of daily extreme temperature and rainfall indices is anchored in a robust theoretical framework that integrates various climate indices, statistical methodologies, and climate models to assess the impacts of climate change on weather extremes. This framework is vital for understanding how climate variability manifests through extreme weather events, particularly in vulnerable regions such as Ethiopia. Climate Extremes Indices serve as the foundation for this framework. These standardized indices quantify temperature and precipitation extremes, allowing for meaningful comparisons across different geographical areas and time periods. According to the World Meteorological Organization (WMO), essential climate indices include metrics for extreme temperatures, such as the number of warm days or cold nights, and for precipitation, such as the frequency of heavy rainfall events (WMO, 2011). These indices help researchers to systematically evaluate changes in climate extremes over time.

Statistical Methods play a crucial role in analyzing trends associated with these climate indices. Techniques such as linear regression analysis, time series analysis, and non-parametric tests are commonly employed to discern significant patterns and anomalies in extreme weather data (Mann, 1977; Wilks, 2011). By applying these statistical approaches, researchers can identify trends that may correlate with broader climatic shifts, thereby enhancing the understanding of how extreme events are evolving in response to climate change. Climate Models, including Regional Climate Models (RCMs) and General Circulation Models (GCMs), are integral to projecting future climate scenarios. These models simulate potential temperature and precipitation patterns under various greenhouse gas emission scenarios, providing insights into how climate extremes may change over time (IPCC, 2013). By utilizing these models, researchers can assess not only the likelihood of extreme weather events but also their potential impact on local ecosystems and human livelihoods.

Another critical aspect of the theoretical framework is the examination of teleconnections. These are the climatic links between global climate indices, such as the El Niño Southern Oscillation (ENSO), and local weather patterns. Research has shown that these teleconnections significantly influence rainfall variability and temperature extremes in regions like the Horn of Africa (Nicholson, 2017; Liebmann et al., 2014). Understanding these relationships is essential for predicting extreme weather events and preparing for their impacts. The framework also encompasses the impact assessment of climate extremes on socio-economic systems. This involves examining how shifts in temperature and precipitation extremes affect agricultural productivity, water resources, and public health (Mastrorillo et al., 2016). Vulnerability assessments are particularly important, as regions that rely heavily on rain-fed agriculture, such as Ethiopia, are more susceptible to the adverse effects of climate variability (Bogale & Erena, 2022).

Finally, the theoretical framework emphasizes the need for developing adaptation strategies to mitigate the impacts of climate extremes. Effective adaptation measures may include improving water management practices, enhancing agricultural resilience through diversification, and implementing early warning systems for extreme weather events (Sahani et al., 2019). By integrating these strategies into policy and planning, communities can better prepare for and respond to the challenges posed by climate change. In summary, the theoretical framework for studying daily extreme temperature and rainfall indices is multifaceted, combining climate indices, statistical analysis, climate modeling, and socio-economic assessments. This comprehensive approach is essential for understanding the complexities of climate extremes and informing effective adaptation strategies in vulnerable regions.

2.1. Data Source and Quality Control

This study made use of gridded daily precipitation maximum and lowest temperature data from the National Meteorological Agency (NMA) within a period of the years 1981 to 2020. This gridded dataset combines locally calibrated satellite-derived data with integrated quality-controlled station data from the National Observation Network. This combined dataset employed the combined product shows improved quality over regions of the country where stations are sparsely distributed (Dinku et al., 2014; Esayas et al., 2018). Because it resolves a significant discontinuity seen in station data during a brief period, this data is recommended for use.

In this study data quality control process of each time series was tested using RClimDex 1.1(Zhang and Yang, 2004). The quality control involves checking errors such as (i) days with negative or greater than 500mm rainfall amount, (ii) minimum temperature equal to or greater than maximum temperature, and outliers, which are values plus or minus four times standard deviation. Accordingly, a station with the best value data quality is considered in the study. After the quality control, the data was used for extreme analysis.

2.1.1. Trend Analysis of Rainfall and Temperature

The Mann-Kendal test was used to evaluate the trend of temperature and precipitation extremes indices. Mann Kendal (Mann, 1945; Kendall, 1975) is the most robust tool for detecting trends because the method is less sensitive to outliers and skewed distributions within time series data (Wang and Swail, 2001). In this study, the Mann-Kendal test was applied for temperature and precipitation data which are not always normally distributed (Yue and Wang, 2004). The trend was tested by computing p-value at a 95% confidence level. The slope of temperature and rainfall extremes were determined using the non-parametric Sen's slope estimator (Sen, 1968). It uses the median slope to assess the trend over time. Sen's slope estimator is widely applied to quantify the slope of rainfall and temperature time series data. Both the Mann-Kendall test and Sen's slope estimator were used to compute trends in hydro-meteorological series. Detailed descriptions of Mann–Kendall and Sen's slope estimation can be found in the related studies (Li et al., 2018; Worku et al., 2019).

$$S = \sum_{i=1}^{N-1} \sum_{j=i+1}^{N} sgn(x_j - x_i)$$

Where N is the number of data points. Assuming $\left(x_j - x_i\right) = \theta$, the value of $sgn(\theta)$ is computed as follows:

$$sgn(\theta) = \begin{Bmatrix} 1\ if\ \left(x_j - x_i\right) > 0 \\ 0\ if\ \left(x_j - x_i\right) = 0 \\ -1\ if\ \left(x_j - x_i\right) < 0 \end{Bmatrix}$$

Where: -Seasonal and annual values in years j and $i, j > i$, respectively. $\left(x_j - x_i\right)$ is the signum function. The test statistic (S) has been assumed to be asymptotically normal, $E(S) = 0$. The equation indicates the increasing and decreasing trend of the data(M.G. Kendall, 1975).

The variance statistic is also calculated as follows: -

$$V(S) = \frac{1}{18}\left[n(n-1)(2n+5) - \sum_{k=1}^{g} t_k(t_k - 1)(2t_k + 5)\right]$$

where n is the number of data points, g is the number of tied groups (a tied group is a set of data having the same value), and t_k is the number of data points in the k^{th} group. The standard test statistics Z is calculated as follows.

$$Z_s = \begin{cases} \frac{S-1}{\sqrt{Var(S)}}, S > 0 \\ 0, \quad S = 0 \\ \frac{S+1}{\sqrt{Var(S)}}, S < 0 \end{cases}$$

The Z_s Value is used to evaluate the significance of the trend variation in terms of decreasing and increasing trends. In the two-sided test under a significant α level, if $|Z_s| < Z_{\left(1-\frac{\alpha}{2}\right)}$, the hypothesis that the sequence X_i has no trend is accepted, but if $|Z_s| > Z_{\left(1-\frac{\alpha}{2}\right)}$, the hypothesis is rejected and the sequence has either an increasing or decreasing monotonic trend. $Z_{\left(1-\frac{\alpha}{2}\right)}$ is the standard normal distribution value when the probability exceeds $1 - \frac{\alpha}{2}$. In this study, a significance level of $\alpha = 0.05$ was adopted; thus, $Z_{\left(1-\frac{\alpha}{2}\right)} = 1.96$.

2.1.2. Sen's slope estimator

Sen's slope estimator the direction and its magnitude (Kocsis et al., 2017) in meteorological time series (Chattopadhyay and Vennila,2015; Pal et al., 2017). It is the non-parametric method that can calculate the change per unit time. This method is used to determine the linear trend of the time series (Pal et al., 2017b). In this method, the slopes T_i of all data pairs are calculated as follows:

$$T_i = \frac{x_j - x_i}{j - i}$$

For i =1, 2,…, N

Where $x_j \ and\ x_i$ are data values at a time j and $i (j > i)$, respectively. If there are n values x_j in the time series and obtained N=n(n-1)/2 slope estimates S_i.The median of these N values of T_i is Sen's estimator of slope, which is calculated as

$$T_{Med} = \begin{cases} T_{\frac{N+1}{2}} \quad N\ is\ odd \\ \frac{1}{2}\left(\frac{T_N}{2} + \frac{T_{N+2}}{2}\right) \ N\ is\ even \end{cases}$$

A positive value of Ti indicates the is an increasing and a negative value of Ti gives a decreasing trend in the time series (Mondal et al., 2012).

2.1.3. Evaluation of Extreme Indices

A statistical examination of variations in the dependent climatological characteristics, including time series analysis and comparison, extremes, and trends, is made possible by extreme climate indices. The RClimDex 1.1 software package was utilized to assess the extreme indices of daily rainfall and temperature time series, focusing on their trend and variance. The Expert Team on Climate Change Detection Monitoring Indices (ETCCDMI), among other worldwide research organizations, created the analysis package for trend and variability evaluation of time series temperature and rainfall data (WMO, 2009). You can get RClimDex, an easily navigable R-based program, from http://etccdi.pacificclimate.org/. Shanghai et al. (2011). Out of the 27 core indices that RClimDex computes daily, the most pertinent 10 temperature indices and 10 precipitation indices for this study.

Table 1: List of temperature and rainfall indices

	Index	Indicator name	Definition of the Index	Units
Rainfall extremes	R20mm	The Number of very heavy rainfall days	Annual count of days when PRCP ≥ 20 mm	Days
	CDD	Consecutive dry days	Maximum number of consecutive days with RR < 1 mm	Days
	CWD	Consecutive wet days	Maximum number of consecutive days with RR ≥1 mm	Days
	R95p	Very wet days	Annual total PRCP when RR > 95th percentile	Mm
	PRCPTOT	Total wet-day rainfall	Annual total PRCP in wet days (RR ≥ 1 mm)	Mm
Temperature	TXx	Max. T_{max}	Annual maximum value of daily maximum temperature	^{0}C
	TNx	Max. T_{min}	Annual maximum value of daily minimum temperature	^{0}C
	TXn	Min. T_{max}	Annual minimum value of daily maximum temperature	^{0}C
	TNn	Min. T_{min}	Annual minimum value of daily minimum temperature	^{0}C
	TN10p	Cool nights	Percentage of days when TN <10th percentile	%
	TX10p	Cool days	Percentage of days when TX < 10th percentile	%

Max. = maximum, Min. = minimum, T_{max} = maximum temperature, T_{min} = minimum temperature, PRCP = precipitation, and RR=daily precipitation.

2.1.4. Global-climate indices

Several large-scale ocean-atmospheric indices have been identified to have teleconnections with the variability of rainfall in Ethiopia (Degefu and Bewket, 2017; Zeleke and Damtie, 2016). Among these climate indices, Sea level pressure (SLP) is increasing/ decreasing in atmospheric pressure at sea level, which can disclose useful information on atmospheric circulation, bringing about wetter and drier conditions. Changes in Sea Surface

Temperature (SST) can also generate a difference in the heat-flux field, bringing about anomalies in atmospheric circulation and rainfall patterns (Copsey et al., 2006). This study selected the most important global climate indices to estimate their association with local precipitation indices. These are: -

a) The global SST anomalies, including the Dipole mode index (DMI), the anomalies of SST between the Western (10°S-10°N and 50°-70°E) and the Southeastern (10°S-0° and 90°-110°E) the equatorial Indian Ocean. The Pacific Decadal Oscillation (PDO) index is the leading principal component of Northern Pacific monthly SST variability (poleward of 20° N in the Pacific Basin), El Niño–Southern Oscillation (ENSO) represented by averaged Niño SST indices, Niño 1+2, Niño 3 (90–150° W and 5° N–5° S), Niño 3.4, and Niño 4 (150° W– 160° E and 5° N–5° S), and

b) Atmospheric pressure at sea level or sea level pressure (SLP), including the Southern Oscillation Index (SOI), and the North Pacific Index (NPI), are the area-weighted SLP over the region 30–65° N, 160° E–140° W, the Trans-Polar index (TPI), and the North Atlantic Oscillation (NAO).

The data were obtained from the National Oceanic and Atmospheric Administration (NOAA) http://www.cgd.usar.edu.cas/catalog/climate/TNI_N 34 index .html.

2.1.5. Correlation of daily extreme indices with global atmospheric circulation

In this study, the Pearson Correlation Coefficient (r) was used to evaluate the link of daily rainfall extreme with global atmospheric indices at a 95% confidence level. Pearson correlation was used to evaluate linear association between two variables x_i and y_i.The Pearson correlation (r) is given by: To prove the formula for the correlation coefficient, we start with its definition and derive it accordingly,

$$\mathrm{Cov(X,Y)} = \frac{1}{n}\sum_{i=1}^{n}(x_i - \bar{x})(y_i - \bar{y})$$

$$\mathrm{Var(X)} = \frac{1}{n}\sum_{i=1}^{n}(x_i - \bar{x})\,2$$

$$\mathrm{Var(Y)} = \frac{1}{n}\sum_{i=1}^{n}(y_i - \bar{y})2$$

$$r = \frac{\{\mathrm{Cov}\}(\mathrm{X, Y}}{\sqrt{Var\ (X).Var(Y)}}$$

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

Where n is the number of observations, x_i,and $y_i$the variable and $\bar{x}$ and $\bar{y}$ are their mean, respectively.

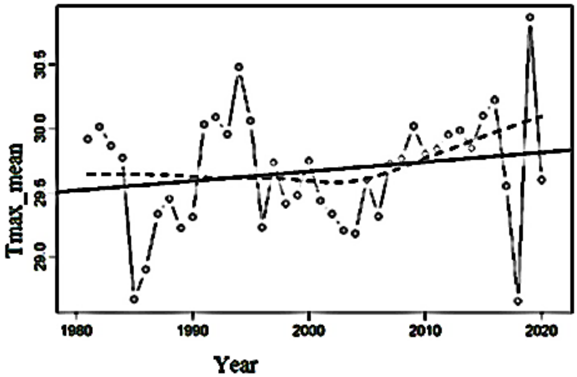
- If X and Y are perfectly positively correlated, r = 1
- If there is absolutely no association, r = 0
- If X and Y are perfectly negatively correlated, r = -1
- Thus -1 ≤ r ≤ 1.
- The closer r is to +1 or -1, the greater is the strength of the association (Freedman, et al., 2007).

3. Results and Discussion

3.1. Temporal and Spatial Trends of Daily Extreme Temperature and Rainfall Indices

3.1.1. Temporal Trend of Daily Extremes Temperature Indices

Fig.1 depicts, the Borena Zone underscores the complex of maximum and minimum temperatures, the dynamics, and their increase of them.


Tmax_mean
30.5
30.0
29.5
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1980
1990
2000
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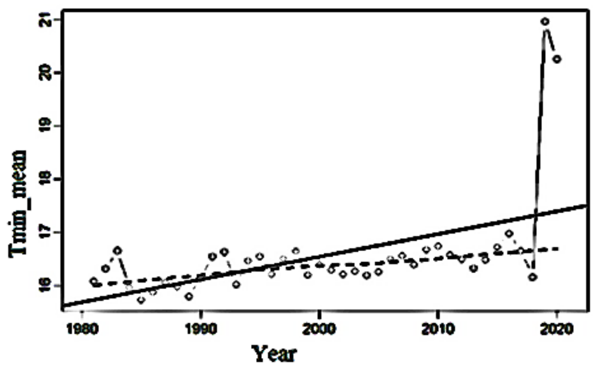
Tmin_mean
21
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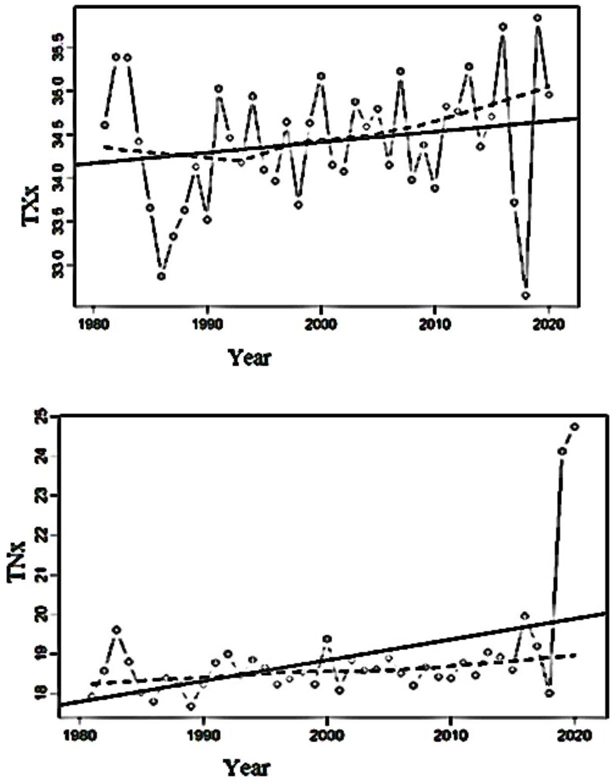
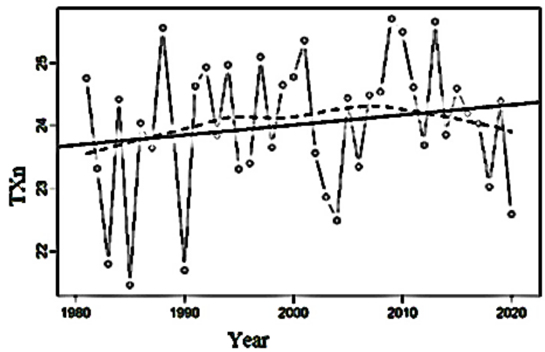
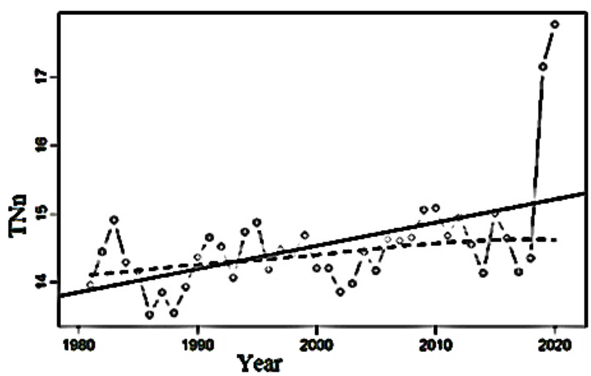


Figure 1: Extreme temperature indices of (T-max mean and T-min mean)

The straight solid line in the figure is the linear trend for each variable for the basin, whereas the dashed line is the moving average. The mean maximum temperature of the area observed an increasing trend with a positive slope, and the annual TMAX-mean increased by 0.057^0C/year. The moving average also depicts the higher variation or anomalies of the maximum temperature in the area from 1981 to 2020. This consistent upward trajectory suggests a shift in climatic conditions that may have profound implications for local ecosystems and agricultural practices. Similarly, the mean minimum temperature in Borena also exhibits a notable upward trend, particularly exaggerated from 2010 onwards, with an annual increase of 0.043°C per year throughout the study period. This annual result is more analysis taken from daily extreme values. Accordingly, the daily maximum temperature (TXX) of Borena shows an increasing trend. The moving average also shows an increasing anomaly except for 1986 and 2018. These anomalies may reflect the influence of specific climatic events or fluctuations that warrant further investigation. The daily minimum temperature (TNX) trend of the area showed that increasing trend and the anomaly also observed an extreme increase, particularly in 2018. In agreement with this study's results' researchers (Asfaw et al., 2018; Belay et al., 2021; Mengistu and Haji, 2015) done on the area reported the highest increase of both maximum and minimum temperatures. These studies corroborate the observed warming trends in current and future temperatures in the region, emphasizing the urgency of addressing climate change impacts.





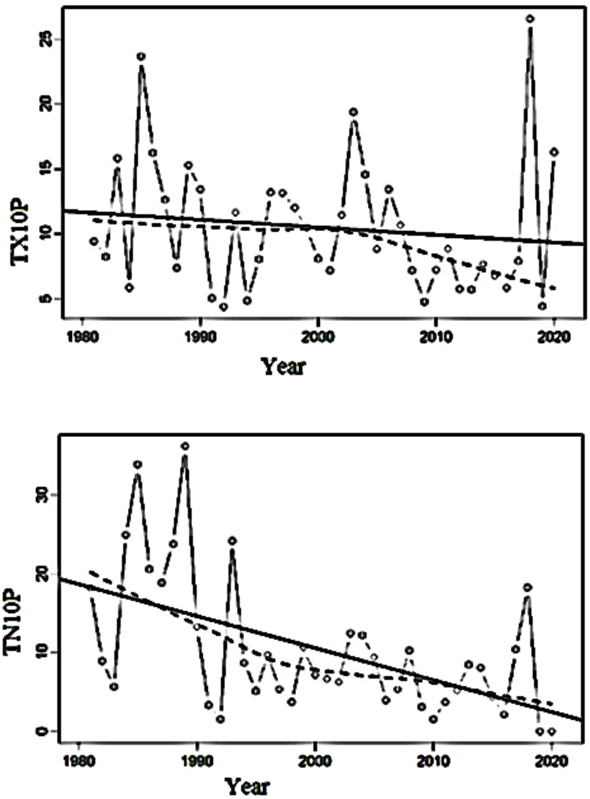


Figure 2: Extreme temperature indices of (TXn, TNn, TN10p and TX10p)

Figure 2 presents the extreme temperature indices, including the monthly minimum value of daily maximum temperature (TXn). The straight solid line in the figure is the linear trend for each variable for the basin, whereas the dashed line is the moving average. The Monthly minimum value of the daily maximum temperature (TXn) observed an increasing tendency, and the moving average shows a decreasing trend. This discrepancy suggests that while the coldest day temperatures are generally rising, there may be periods of fluctuation that require closer examination. Thus, the TXn or the coldest day significant variation has been observed or considerable anomalies recorded in the study area (Fig.2). Similarly, research done by (Mekasha et al., 2014) noted a similar trend as both increasing and decreasing trends have been recorded. The coldest night (TNn) showed a very significant increasing trend, and the anomalies of the moving average observed a significant increasing trend, particularly in the 2019 year. Esayas et al. (2018) reported a similar result that shows an increase in the coldest day (TNn) in southern Ethiopia. Both cool day (TX10P) and Cool night (TN10P) depicted a very decreasing trend that agreed on the increment of warm night and warm day. This trend underscores a broader shift towards warmer nighttime temperatures, which can have critical implications for nocturnal ecosystems and energy consumption patterns. Supporting these findings, Damtew et al., (2022) stated the decline of cold extreme temperature indices in cool days (TN10p) and cool nights (TX10p). These extreme climate events make people suffer from continuous drought (Dejene et al., 2023).

Overall, these results highlight the pressing need for adaptive measures to mitigate the impacts of increasing temperature extremes, particularly in vulnerable regions like Borena. Understanding these trends is essential for developing effective climate adaptation strategies that can enhance resilience among local populations.

3.1.2. Spatial Trend of Daily Extremes Temperature Indices

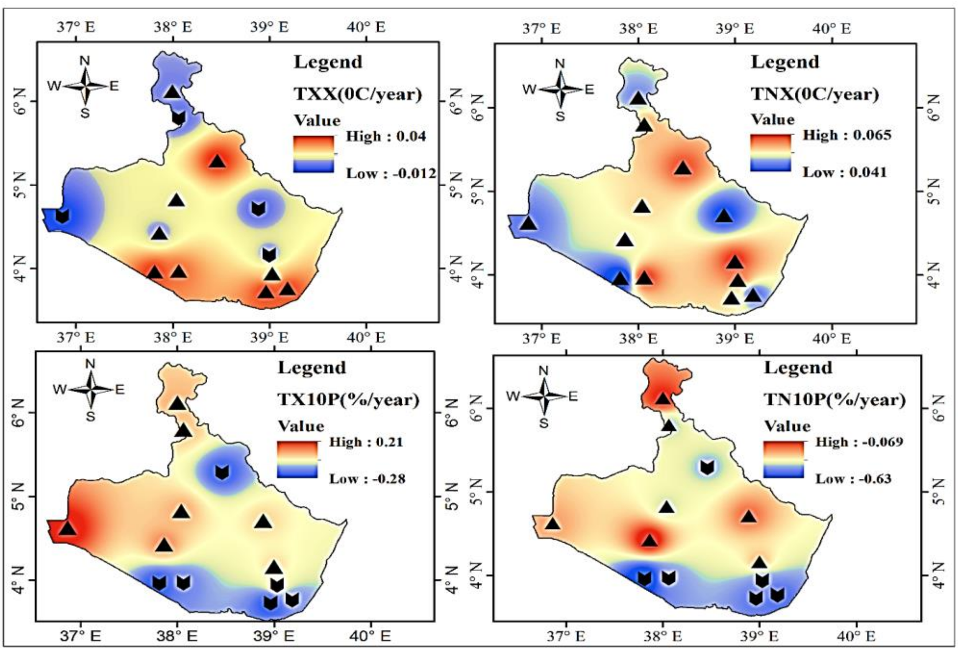
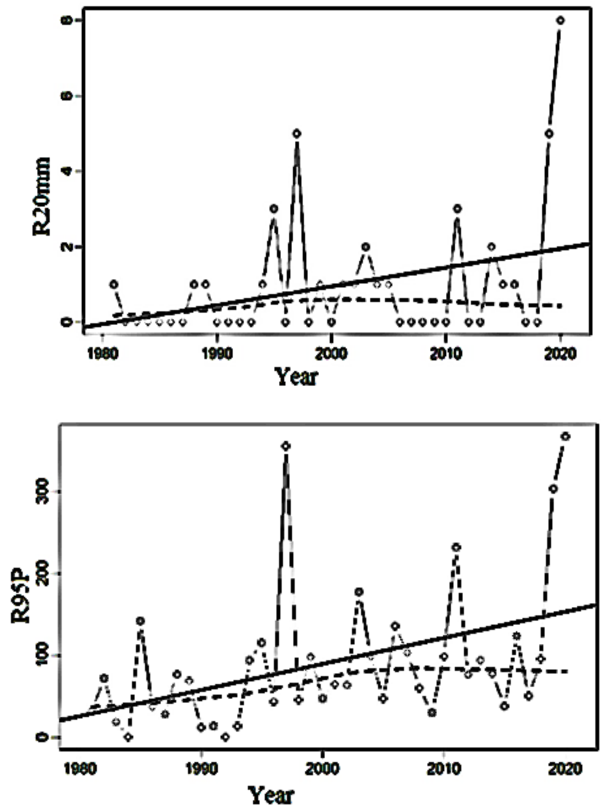


Figure 3. Spatial variations of extreme temperature indices of TXx, TXn, TNx, and TNn trends in °C/year of Borena for the years 1981-2020.

The triangles and the down-arrow in the pictures indicate significant increasing and decreasing trends at the 5% level, respectively. In the northern humid and central moist part of the zone, the maximum value of the maximum temperature (TXx) shows a decreasing trend with 0.0120c/year. This decline may be influenced by localized climatic factors, including land use changes and variations in precipitation patterns. Conversely, in the central, the west semi-arid, and the east arid regions TXx trend value increased significantly ($p<0.05$) with 0.04^0C/year. The trend for the maximum daily minimum temperature (TNx) across the study area reveals an increasing pattern ranging from 0.041°C to 0.065°C per year. Such increases in TNx are critical, as they suggest a general warming trend that affects not only daily temperatures but also nocturnal ecosystems. The regional trends of the two indices, TXx and TNx, show stout increases trend. The percentages of cool days (TX10p) and cool nights (TN10p) showed strong variability that depicts the increasing and decreasing trend; however, both showed decreasing in the southern area in common (Fig.3). This decline in cool extremes is particularly concerning, as it may lead to reduced agricultural resilience and increased vulnerability to heat-related stress among local populations. Previous studies (Esayas et al., 2018; Mekasha et al., 2014; Mohammed et al., 2022) on temperature extreme indices in the area confirmed the result obtained in this research. Increasing trend of warm extreme indices and decreasing trend of cold extreme indices (TN10p and TX10p) were observed. The consistency of these results across different studies highlights the reliability of the data and the urgency of addressing the implications of these temperature changes. The trends in mean annual maximum and minimum temperatures, along with various extreme temperature indices, confirm a pronounced warming trend in the area. Overall, the daily extreme temperature trends in the eco-environments of the study area indicate a rise in warm extremes and a decline in cold extremes. These shifts necessitate immediate attention to adaptation strategies that can mitigate the impacts of changing temperature patterns on local ecosystems and communities.

3.1.3. Temporal Trend of Daily Extremes Rainfall Indices



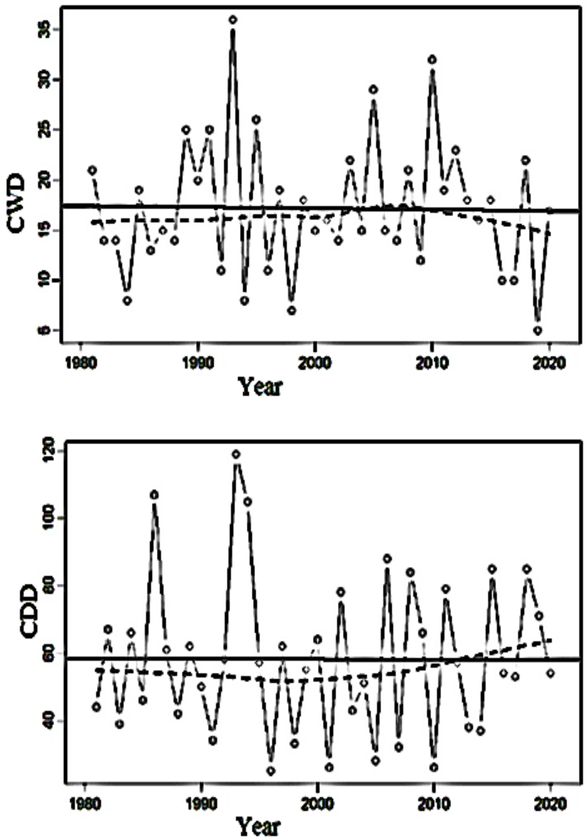


Figure 3: Extreme rainfall indices of (R20mm and R95p, CWD, CDD)

Figure 4 illustrates the extreme rainfall indices, presenting both the linear trend and moving average for each variable in the basin. The number of very heavy rainfall days (R20mm) shows an increasing trend with a slope of 0.05 mm/year. This upward trend indicates a potential shift in rainfall patterns, suggesting that heavy precipitation events may become more frequent in the region. However, the moving average showed the highest fluctuation of anomaly and almost below-average value except for the higher increase shown in 2018. The very wet day (R95p) observed a significant increasing trend of 2.044mm/year. This substantial increase may enhance the risk of flooding and soil erosion, particularly in vulnerable landscapes. The moving average depicted the strongest variation anomalies, and mainly in 1998 and 2018, it showed the highest value above the average. Continuous wet day (CWD) value in the study period never showed an increasing or decreasing slope; however, the moving average showed a variation and a decreasing trend since 2010. This decline in continuous wet days may have serious implications for water availability and agricultural productivity. On the contrary, the value of continuous wet days observed a decreasing trend of 0.013 mm/year. The value of continuous dry days (CDD) also showed an increasing trend with considerable anomalies, particularly since 2016, when it was above average (Fig.4). The increase in CDD is particularly concerning as it suggests prolonged dry spells, which can exacerbate drought conditions in the region. Similar to these results, the study done by Dendir and Birhanu (2022); Kiros et al.(2017); Mohammed et al.(2022) in the same agroecological zone found the increment of R20mm, R95p, and the decrease of CWD as well as the increment of CCD in southern Ethiopia The emphasis on the recent increases in CDD and declines in CWD highlights the growing concern for drought occurrences in the area, necessitating urgent adaptive measures to mitigate adverse impacts on agriculture and water resources.

3.1.4. Spatial Trend of Daily Extremes Rainfall Indices

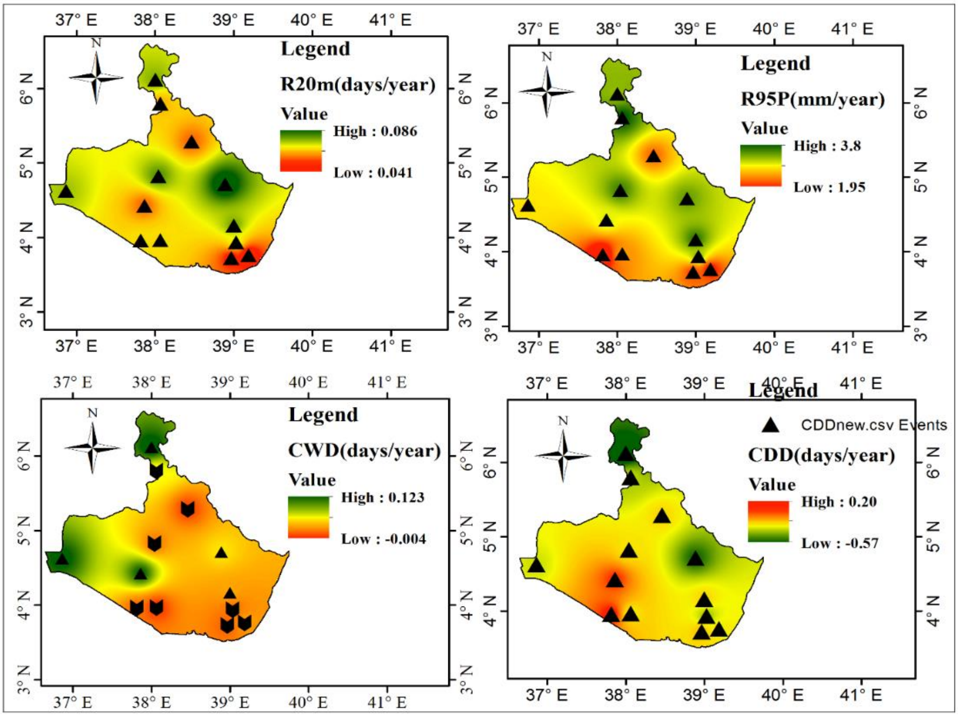


Figure 4: Spatial variations of rainfall extreme indices trends of R20mm (days/year), R95P(mm/year) both in mm/year, trends in CWD (Days/year), and trends in d CDD (days/year) of Borena for the duration of 1981-2020.

Figure 5 illustrates the spatial trends of the extreme rainfall indices R20mm, R95p, CWD, and CDD across the Borena Zone. The triangles and the down-arrow in the pictures indicate significant increasing and decreasing trends at the 5% level, respectively. The spatial trend of R20mm, R95p, CWD, and CDD in Fig.2.5 showed very different values in humid, moist, semi-arid, and arid regions of the Borena Zone. Accordingly, the R20mm value showed a significant (p=0.03) increasing trend in most parts of the study area with 0.05mm/year. This trend suggests a potential enhancement in heavy rainfall events, which could impact local water management and agricultural practices. However, there is an insignificant decreasing trend observed in the southeast (arid) part of the zone.

The R95p index demonstrates a significant ($p = 0.006$) increasing trend of 3.183 mm/year throughout the zone. Such an increase in extreme precipitation could exacerbate flooding and soil erosion risks, particularly in vulnerable landscapes. The continuous wet-day index (CWD) shows a decreasing trend of 0.013 days/year, with exceptions noted in the western semi-arid and northernmost regions, indicating localized variability in wet-day patterns.

In contrast, continuous dry days (CDD) exhibit an increasing trend, except for the central moist regions. This increase in CDD points towards prolonged dry spells, which are concerning for water availability and agricultural productivity in the region.

In line with this result, studies done by (Adem and Amsalu, 2021; Amsalu and Adem, 2009; Gemeda et al., 2022) found the erratic rainfall and the increment of warming conditions of the area caused extreme drought and other climate hazards. These findings underscore the urgent need for adaptive strategies to mitigate the impacts of these climatic changes on local communities and ecosystems.

3.2. Correlation of daily extreme indices with global atmospheric circulation

Regional climate change, particularly the variation and change of daily extreme rainfall, is significantly influenced by global atmospheric climate indices such as Sea Surface Temperature (SST) and Sea Level Pressure (SLP) (Kebede and Bewket, 2009).

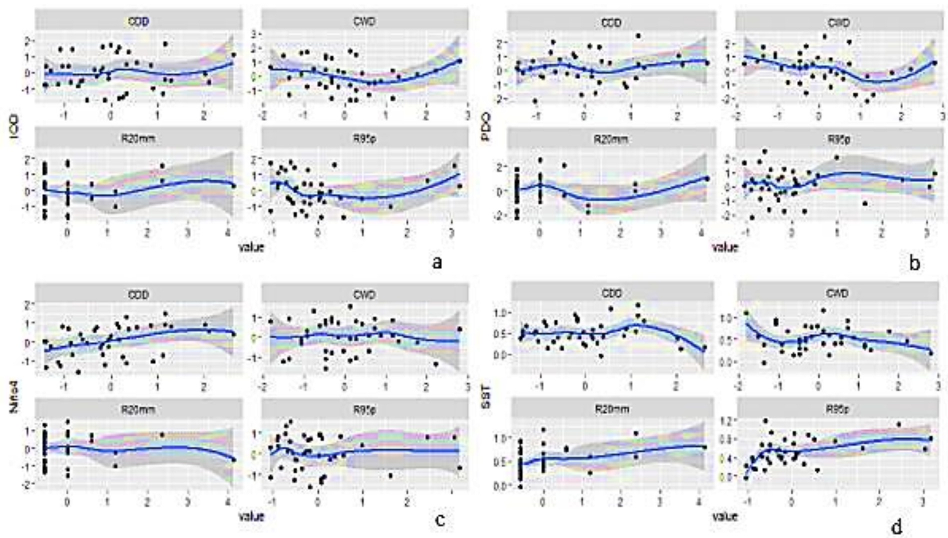


Figure 5: The correlation of global indices (IOD, PDO, NINO 4, and Global SST) with daily extreme rainfall CDD, CWD, R20mm, and R95sp) of the Borena zone in the period of 1981 to 2020.

Fig.7 shows the correlation between SST groups, which include IOD, PDO, NINO 4, and Global SST itself. Hence, Nino 4 and global SST had a negative correlation with CWD and showed a significant positive correlation with CDD (r=0.36 and 0.41) with a 95% confidence level. This suggests that as warm ocean temperatures increase, the occurrence of continuous wet days decreases, leading to dryer conditions. The remaining large-scale climate indices, IOD and PDO, showed almost the same pattern: There was a negative correlation with CWD and a negative correlation with extreme daily rainfall indices. This result exhibits a negative correlation with wet days, suggesting the decreasing extreme rainfall in the area. These findings indicate a concerning trend towards decreased wet days, suggesting a decline in extreme rainfall events in the area. The positive correlation between CDD and the negative correlation with CWD showed the warmed or drought tendency of the study area. This pattern observed a tendency towards warming or drought events. This analysis of SST groups depicts the connotation between extreme rainfall indices and global climatic factors in the Borena zone showed different patterns. It observed a warming tendency as NINO 4 and global SST clearly correlate with more dry spells and fewer wet days. Furthermore, highlighting the trend toward warmer or drier conditions in the study area, IOD and PDO also contribute to this pattern by demonstrating negative associations with CWD and daily rainfall extremes. In agreement with these findings, studies done by Beyene et al.(2022), Degefu et al.(2017), and Tashebo et al.(2021) stated that the recent global SST variation has led to a severe extreme impact in lowland pastoralist areas, including the Borena zone.

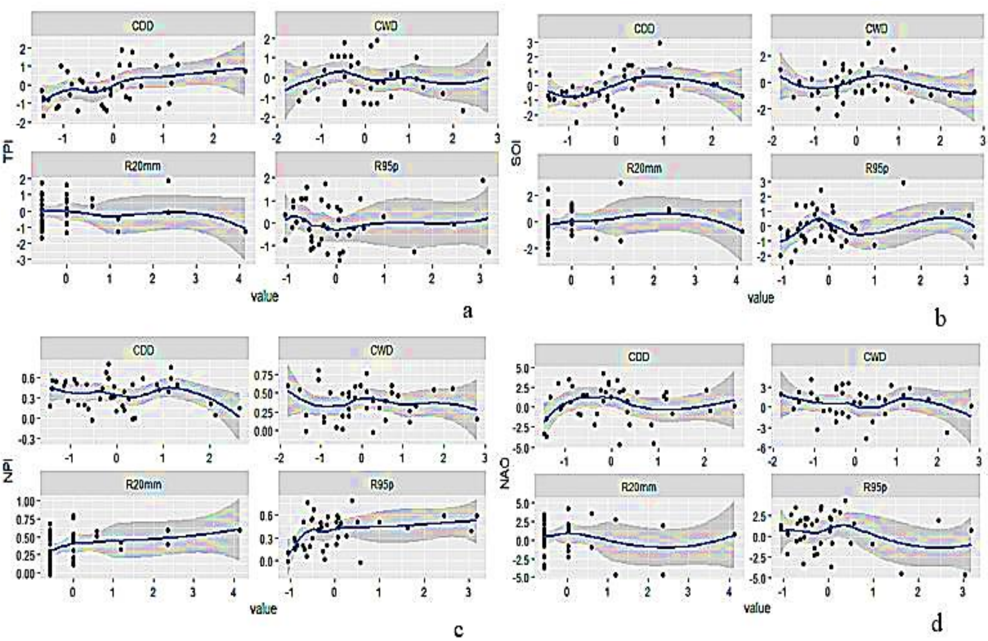


Figure 6: The correlation of global indices (TPI, SOI, NPI, and NAO) with daily extreme rainfall CDD, CWD, R20mm, and R95sp) of the Borena zone in the period of 1981 to 2020.

Figure 7 shows the correlation of sea level pressure (SLP), including TPI, SOI, NPI, and NAO. Accordingly, TPI had a negative correlation with

R20mm and R95p and made a positive significant correlation with CDD (r=0.435), which is responsible for the drying of the area. The SOI has a negative correlation with CWD and made positive correlation with CDD, R20mm, and R95p. The NPI had a negative correlation with CWD and made a positive correlation of R20mm and R95p. The NAO presents a positive correlation with CDD while correlating negatively with other daily extreme rainfall indices. This finding observed SOI, TPI, and NAO correlation values with daily rainfall indices of the area associated with prolonged dry spells, leading to warming (drought). It confirms the complex correlation between global climate indices and extreme daily rainfall indices that affect the wet and dry spells in the area. The correlation analysis of sea level pressure (SLP) indicators, including TPI, SOI, NPI, and NAO, with daily rainfall indices provides useful insights into their influence on precipitation extremes in the research area. The negative correlations of TPI, SOI, and NPI with cumulative wet days (CWD) imply a decline in wet day occurrences during periods of high index values, pointing to a drying trend. Conversely, the positive correlations of these indicators with heavy rainfall and consecutive dry days (CDD) indices (R20mm and R95p) suggest an increased likelihood of extended dry spells and severe rainfall events during those periods. In summary, the findings align with previous research by Anose et al.(2022) and Hou et al.(2023), which highlights that SLP anomalies are closely associated with climate conditions in the southern regions, contributing to prolonged dry spells and fewer occurrences of heavy rainfall.

4. Conclusion

Evaluating the temporal and spatial trends of temperature and precipitation extremes at a fine resolution is crucial for effective management and decision-making across various sectors, particularly in water resource management and agriculture. This study examined the daily extreme indices in the Borena Zone from 1981 to 2020, revealing significant increases in both temporal and spatial extremes of temperature. Notably, while the mean maximum and minimum temperatures exhibited substantial upward trends, the indices for cool days (TX10p) and cool nights (TN10p) showed only slight increases, further exacerbating the region's warming situation. The analysis of spatial and temporal trends indicates a concerning pattern: a decrease in continuous wet days (CWD) alongside an increase in continuous dry days (CDD). These findings suggest a shift towards more prolonged dry spells, which have significant implications for local ecosystems and agricultural practices. Additionally, the evaluation of the correlation between daily extreme rainfall indices and global climate indices revealed that large-scale atmospheric patterns, such as Sea Surface Temperature (SST) and Sea Level Pressure (SLP), significantly influence regional climate variability. Specifically, the positive correlation of SST and SLP with CDD indicates an increasing likelihood of extended dry spells, while the negative correlations with CWD highlight a decline in wet day occurrences, suggesting a trend towards aridity. Understanding the relationships between regional climate variables and large-scale climate indices is essential for developing effective adaptation strategies in response to these climatic changes. The findings underscore the urgent need to address the impacts of extreme temperature and rainfall events, which pose challenges to infrastructure, agricultural productivity, and water resource availability. Furthermore, the documented erratic rainfall patterns and rising temperatures in the Borena Zone call for further research to quantify the magnitude of these extreme events and their implications for climate variability in the region.

In conclusion, proactive measures must be implemented to mitigate the risks associated with these climatic phenomena, ensuring sustainable management of resources and resilience in the face of ongoing climate change.

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