Extreme Rainfall Indices and its Effect on *Meher* Season Crop Calendar: An Agro-Climatic Zone Based Study

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ABSTRACT

The study analyzed the daily extreme rainfall indices and its consequences on Meher (summer) season cereal crop calendar in the agro - climatic zones (ACZs) of a watershed. Long-term (1981–2019) rainfall data for 50 sample grid points with a spatial resolution of 5 5 km from Climate Hazards Group Infrared Precipitation (CHIRPS) was considered. Focus group discussions were employed to identifying the local crop calendars and consequences of extreme rainfall events. Mann Kendall's (MK) and Sen's slop statistics were used to define the trends, statistical significance, and magnitude of the changes in extreme rainfall indices. The upward and downward signals were found for different crop calendars of the ACZs. Most of the increasing trends were observed for the land preparation period (LPP), sowing and management period (SaMP), and harvesting and threshing period (HaTP) field operations in the highland zone, midland zone, and all ACZs, respectively. In contrast, some of the downward trends in extreme rainfall indices were observed for LPP and SaMP in the cold-highland zone and highland zone, and HaTP was observed to be the same in all ACZs. The upward and downward signals of the indices could have negative consequences for existing cereal crop production in the watershed.

Keywords | agro-climatic zones, climatic hazard, crop calendar, rain-fed agriculture

INTRODUCTION

Climate-related extremes have been the dominant trigger of natural disasters in the Horn of Africa region, particularly in Kenya, Ethiopia, and Somalia (Omondi *et al.*, 2014). Annual rainfall projections show a robust increase in precipitation over Somalia and a less robust decrease over central and northern Ethiopia (Hoegh-Guldberg *et al.*, 2018). The number of consecutive dry days (CDD) and consecutive wet days (CWD) is projected to increase and decrease, respectively (Liebmann *et al.*, 2014). The drying trend of East Africa's long rains in recent decades arises from natural decadal variability (Lyon, 2014).

The decadal variability in the region can be explained by the decadal variability of sea surface temperature (SST) in the Pacific Ocean(Yang *et al.*, 2014). SST variability associated with El Niño-Southern Oscillation (ENSO)is the largest source of forcing for seasonal drought in the Horn of Africa (Lyon, 2014). Within the region, the fluctuations in rainfall intensity are largely associated with East-West adjustments in the zonal walker circulations that are linked to ENSO (Omambia *et al.*, 2017). In contrast, the precipitation increase is mostly due to western Indian Ocean warming (Liebmann *et al.*, 2014).

Evidence generated from empirical observation (Mika, 2013) and model studies(Omondi *et al.*, 2014; Yu *et al.*, 2018) confirms that the frequency, intensity, timing, and geographical extent of extreme climate phenomena (e.g. droughts and floods) have been changing. Similarly, there are changes in the number of wet and dry days, length of wet and dry spells, rainfall intensity, and warmest days and nights (Libanda, 2020). The changes in these extreme climate phenomena vary across space and time, and so do the impacts(Tierney *et al.*, 2013). In the meantime, the demand for information on local climate extreme events became essential in the current time due to the increasing impacts of the hazard on agricultural activities.

Several studies on climate extremeevents in the world have reported the presence of spatial and temporal variation. For instance, Wu *et al.* (2014)reported generally upward trends for annual simple daily intensity index (SDII), maximum 1-day precipitation ($R \times 1$ day), and maximum 5-day precipitation ($R \times 5$ day), while downward trends for consecutive dry days (CDD) between the period 1969-2011.

Earlier studies on the climatic hazards (Megersa *et al*., 2020; Geremew *et al*., 2020; Berhane *et al*., 2020) showed the presence of complex trends for extreme rainfalls. This is particularly evident in mountainous countries like Ethiopia where significant variation in climatic conditions exists within short horizontal distances mainly due to complex topographic features (Dinku *et al.*, 2014). Analyses of climate extremes in the past have largely been made at conventional temporal scales (annual, seasonal, and monthly), which in most cases do not fit with local crop calendars of various agro-climatic zones. The indicated scale of analysis would not be appropriate for developing adaptation strategies for a specific field operation (land preparation, sowing, crop management, harvesting, and threshing) in given agro-climatic zones (ACZs).

The influences of climate variation on rainfall in Ethiopia are more on its distribution and timing than the annual total amount (Asfaw *et al.*, 2018). The Northwest part of Ethiopia is characterized by unpredictable and erratic rainfall patterns, severe land degradation, a high degree of poverty, and frequent crop failure (Ayalew *et al.*,2012). Abiya watershed consists of various ACZs and is situated in the top part of the Northwest highlands of Ethiopia.For reasons related to rainfall variability, the local farmers face various problems in their farming activity.

As stated by Wu *et al.* (2014), the trend of a series of rainfalland its impact is usually detected by a certainspecific period. Furthermore, it has been recognized that the same extreme rainfall event has a varying impact on crops not only depending on how extreme it was but also when the event happened (Yu *et al.*, 2018). This implies the fact that extreme climatic conditions could directly govern key field operations/crop calendars over a particular period and ACZs. Yet, there is no adequate published study conducted on extreme rainfall indices and their consequences on crop calendar/field operations over various ACZs of Ethiopia.Taking into account its geographic location and composition of ACZs, the Abiya watershed is considered to be a site that can represent the larger context of Northwest Ethiopia and other highlands of the country too. Therefore, the present study is designed to analyze extreme rainfall indices and their consequences on the crop calendar taking into account the case of the ACZs of Abiya Watershed, Northwest highlands of Ethiopia.

STUDY AREA AND DATA SOURCES

Study area

The Abiya watershed is located in northwest Ethiopia within 10°43′0″ to 11°15′ 0″ N latitude and 37°25′0″ to 37°55′0″ E longitude, the Upper Blue Nile basin (UBNB), Ethiopia (Figure 1). The watershed covers an area of 1819km^2.Its elevation ranges from 1,500 4,084meters. Following MoA (2000), this study adopted the traditional ACZs grouping approach. The ACZs of the watershed consistof midland, highland, and cold-highland zones by using the digital elevations model (DEM 30m). The annual temperature of the watershed contains a mean annual minimum of 10.7℃ and a maximum temperature of 23.7℃. The mean annual rainfall was 1324mm.

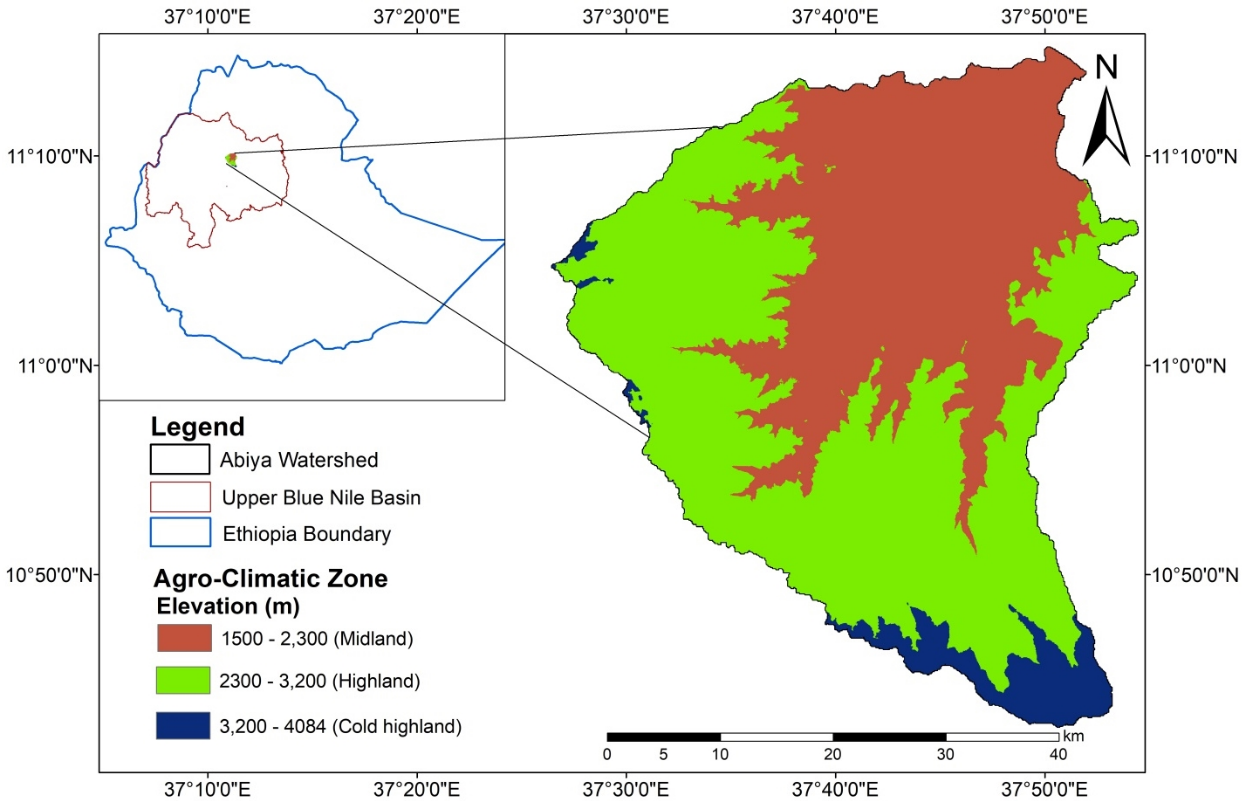

Figure 1| Location map of the agro-climatic zones (elevation in meters) of the Abiya watershed.

The topography of the watershed is characterized by its terrain's highly undulated topography and it consists of mountains, deep gorges, escarpments, and plateaus.The majority of the people in the watershed were engaged in mixed agriculture (crop cultivation and livestock rearing). In the Amhara Regional State, where the study site is situated, the average family size is expected to be 4.6 people, while the population density is expected to be ~189.4 people km^{-2}(BoFED, 2014), based on this it is better to project the total population reside in the watershed. The total population of the watershed is □344,572.

Data sources

DEM

To delineate the agro-climatic zones and calculate their area coverage, DEM30m was used (Table 1).

Table 1 | Spatial coverage of the ACZs of the Abiya watershed

ACZs	Midland	Highland	Cold-highland	Watershed
Elevation (m a.s.l.)	1500- 2300	2300-3200	3200-4084	1379 – 4084
Area (ha)	77,057	95527	9344	181,928
%	42.4	52.5	5.1	100

CHIRPS satellite data

Climate station databasesof Ethiopia have many missing values (Asfaw *et al.*, 2018), do not have adequate data records to support trend analysis (Alemayehu and Bewket, 2017); and do not provide timely and sufficient rainfall pattern data due to the scattering of observations, uneven allocation, and data gaps in the original dataset (Fenta *et al.*, 2018). Accordingly, it became mandatory to employ an alternative rainfall data source. Nowadays, there are several satellite-based rainfall products with varying spatial and temporal resolutions as viable alternatives to rain gauge data. CHIRPS is a relatively new rainfall dataset with high spatial (0.05^o) and temporal (daily) resolution. The dataset is derived from multiple data sources, covering 50^o S and 50^o N from 1981 to the present.

Validations of CHIRPS have been conducted in different parts of the world and the studies have shown satisfactory results. For example, the performance of the CHIRPS dataset was validatedby Dinku *et al*. (2018) in contrast to 1200 reference rain gauge measurements from Ethiopia, Kenya, and Tanzania and informed that CHIRPS was better than most high-resolution satellite products of rainfall data in several regions of East Africa. Likewise, in the study area CHIRPS has been validated widely and has confirmed strong performance when assessed at station locations across the country Lemma *et al.* (2019) in Ethiopia, Taye *et al.* (2020) in UBNB, and Alemu and Bawoke (2020) in the Amhara region, respectively. Thus, in this study, the CHIRPS rainfall data has been used without validation.

A record of daily rainfall data for this study was taken from 50 sample grids points (each representing areas of 5 × 5 km) to study from the CHIRPS dataset, which was accessible online at http://climexp.knmi.nl/select.cgi?field=chirps_20_25.All of the grids points (Figure

2) cover the period between 1981 and 2019 and the grids points were stratified into three ACZs (21 grids points from midland, 26 grids points from highland, and3 grids points from cold-highland) purposively to represent the rainfall conditions of each ACZs of the study area, respectively.

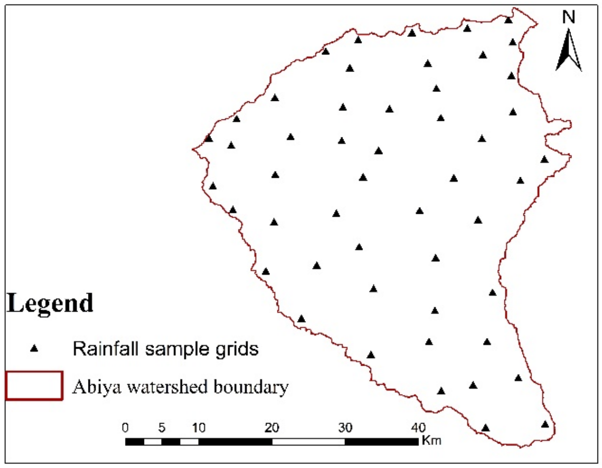

Figure 2| Sample grids were considered for collecting rainfall datasets in the Abiya watershed

Local farmers

In the context of the Northwest highlands of Ethiopia, focus group discussion (FGD) is the best way of generating primary information/data about the situation of the locality. The national database of Ethiopia is very fragmented and doesn't aggregate information at the micro watershed and agro-climate zone level. Accordingly, the qualitative dataset of the current study was collected employing Focus Group Discussions (FGDs). FGDs were made to identify the dominant summer season cereal crops and their crop calendar, and possible consequences of extreme rainfall on the crop calendar in the three ACZs of the watershed. One FGD was made in each of the ACZs. Each FGDconsists of eightparticipants. Participants were chosen to take intoaccount their ACZ to capture their crop calendar (from land preparation to harvesting and threshing period), and possible consequences of extremerainfallindices. To gatherdataregardingthe existing climate variability, elders (>50 years old) were purposely included in the FGDs.

METHODS

Extreme rainfall indices analysis

Eight daily rainfall indices were defined and used, which weredeveloped by the joint commission for climatology (CCI)/ the Climate Variability and Predictability (CLIVAR)/ the Joint Commission for Oceanography and Marine Meteorology (JCOMM) Expert Team on Climate Change Detection and Indices (ETCCDI). The selection was carried out based on the potential impacts on cereal crops and significant references given by the World Meteorological Organization (WMO, 2009). Additionally, extreme rainfall indices that bases on absolute thresholds provide better information relevant to impact studies than indices with percentile thresholds that are more suitable for spatial comparison.

INSTAT+ software (version 3.36) designed to support the analysis of climatic data developed by the previous study (Stern *et al.*, 2006) was used to compute the selected extreme rainfall indices (Table 2). The indicated rainfall indices (Table 2) are calculated from the daily data set for the period 1981-2019 as per the calculation procedures provided by the ETCCDI (HTTP: //etccdi.pacificclimate.org/list_27_indices.shtml).

Table 2 | Definitions of selected extreme rainfall indices

Indices	Name	Definitions	Unit
R × 1-day	Maximum one-day precipitation	maximum one-day precipitation in a crop calendar	mm
R × 5-day	Maximum five-day precipitation	maximum consecutive five-day precipitation in a crop calendar	mm
SDII	Simple daily intensity index	mean precipitation amount on a wet day in a crop calendar, where a wet day is a day with precipitation ≥ 1 mm	mm/day
R10mm	Heavy precipitation days	count of days with precipitation amount ≥ 10 mm in a crop calendar	Days
R20mm	Very heavy precipitation days	Maximum count of days with precipitation amount ≥ 20 mm in a crop calendar.	Days
CDD	Consecutive dry days	maximum count of consecutive days with precipitation amount <1 mm in a crop calendar	Days
CWD	Consecutive wet days	maximum count of consecutive days with precipitation amount ≥ 1 mm in a crop calendar	Days
PRCPTOT	Total precipitation on wet days	Total precipitation amount on wet days in a crop calendar	mm

Serial Autocorrelation Test

Trend detection in time series requires data that is random and persistence-free Ngongondo *et al.* (2011) to solve the confounding effect of serial dependence when interpreting the results. To avoid the influence of serial autocorrelation on the Mann–Kendal (MK) trend test, serial autocorrelation should be checked before applying the MK trend test. Therefore, in this study, the rainfall time series for each ACZ was tested for randomness and independence using the autocorrelation function as described in Von Storch (1999) as follows:

$$r_k = \left[\frac{1}{n-1}\sum_{i=1}^{n-k}(X_i-\overline{X})(X_{i+k}-\overline{X})\right] \Big/ \left[\frac{1}{n}\sum_{i=k}^{n}(X_i-\overline{X})^2\right]$$

(1)

Where $r_k$is the lag−k autocorrelation coefficient, $\overline{X}$ is the mean value of a time series $X_{i,}$ n is the length of data set, and k is the time lag. Random series have autocorrelations near zero for all time-lag separations, except the zero-lag coefficient, which is always one. In that case, statistical tests are directly applied to the series. Non-random series have one or more significantly non-zero autocorrelation values, and statistical tests, in this case, are applied to a pre-whitened series to account for the non-randomness (Fiwa *et al.*, 2014).

Mann–Kendall test (MK)

The values of the indices were subjected to the non-parametric MK test to detect the statistical significance of the trends throughout the observation. MK test is a non-parametric statistical test that is a widelyfunctional and the most effective way to define whether a time series has a monotonic ascending or descending trend (Feng *et al.*, 2016). It is also a lesser amount ofsensitivity to outliers or robustness against the influence of extremes (Poudel and Shaw, 2016). The previous studies (Feng *et al*., 2016; Poudel and Shaw, 2016) indicated that the test does not assume the data to be distributed according to any particular rule; it is not affected by missing data, irregular spacing of the time points of measurement, and the length of the time series.

It is recognized in Feng *et al.* (2016) that the MK statistic *S*, the variance statistic Var (σ), and the consistent standard normal test statistic *Z* could be considered as follows:

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

Where n is the length of the dataset,x_i and x_j are two elements of the measured time series at the time step i and j, respectively, and

$$sgn(x_j - x_i) = \begin{cases} -1, (x_j - x_i) < 0 \\ 0, (x_j - x_i) = 0 \\ 1, \ (x_j - x_i) > 0 \end{cases} \quad (3)$$

If the dataset is identically and independently distributed, then the mean of *S* is zero and the variance of *S* is given by

$$Var(S) = \frac{1}{18}[\, n(n-1)(2n+5) - \sum_t t(t-1)(2t+5)] \quad (4)$$

Where n is the length of the dataset, m is the number of tied groups (a tied group is a set of sample data having the same value) in the time series and ti is the number of data points in the i^{th} group.

The Z statistics are computed using the formula

$$Z = \begin{cases} \frac{S+1}{\;} & for\ S < 0 \\ 0 & for\ S = 0 \\ \frac{S-1}{\;} & for\ S > 0 \end{cases} \tag{5}$$

The positive and negative Z values indicate increasing and decreasing trends, respectively. A significant level α is used to test the monotonic trend. The obtained trend is statistically significant at the 99 % confidence level ($\alpha = 0.01$) if $|Z|$>2.58, at the 95% confidence level ($\alpha = 0.05$) if $|Z|$>1.96, and at the 90% confidence level ($\alpha = 0.1$) if $|Z|$>1.65 (Mandale *et al.*, 2017).

Sen's Slope Estimator

It is a non-parametric procedure used to quantify trend magnitude in time series data. It is a more robust estimator than others because of its relative insensitivity to extreme values (Chattopadhyay and Edwards, 2016). Sen's slope estimator has been commonly used for determining the trend magnitude in hydro-meteorological time series (Jain and Kumar, 2012). It limits the influence of missing values or outliers on the slope as compared with linear regression (Alemu and Bawoke, 2020; Bayable *et al.*, 2021). For a given time series $X_i = x_1$, x_2, x_3, ...,x_n, having N pairs of data, the slope is computed as

$$\beta_i = \left(\frac{x_j - x_i}{j - i}\right), i = 1, 2, 3, \ldots N, j > i, \tag{6}$$

The Sen's Slope β represents the median of the slope values β_i and is calculated as

$$\beta = \begin{cases} \beta_{\frac{N+1}{2}}, & if\ \ N\ is\ odd \\ \left(\frac{\beta_{\frac{N}{2}} + \beta_{\frac{N+2}{2}}}{2}\right), & if\ N\ is\ even \end{cases} \tag{7}$$

The sign of β reflects the data trend direction, whereas its value indicates the steepness of the trend (Alemu and Bawoke, 2020).

RESULTS AND DISCUSSION

Consequences of extreme rainfall indices on crop calendar

Identifying crop calendar

As per the data/information generated from the local farmers through FGDs, the local farmers told their crop calendar namely, the land preparation period (LPP), sowing and management period (SaMP), and harvesting and threshing period (HaTP) were found to be the major local crop calendar for cereal crop production practices. The dominant *Meher* (Summer) season cereal crops such as barley (*Hordeumvulgare*) from cold-highland, wheat (*Triticumspp*), maize (*Zea mays*) from highland, and teff (*Eragrostistef)* and maize (*Zea mays*) from midland zones were identified through FGDs. *Meher* season crops refer to crops that are harvested between September and February, so a study like this has a paramount advantage for places like Ethiopia where rain-fed agriculture is dominant. The members of FGDs had first looked intodifferent field activitiesfrom LPP toHaTP. Then, bearing the normal rainfall distributions annually in the notice, they defined a typical period for each field operation though certain overlaps normally exist in the transitions.

The rainfall distribution in a given year is 'normal' for farmers in the study watershed if its rainfall beginning, interval, offset times, quantity, and distribution jointly form a favorable environment for them to practice all the essential crop production successfully. Later on, the key field jobs were categorized into LPP, SaMP, and HaTP mainly based on their adjacent similarity in terms of rainfall necessities. The first and end dates for each farming period were defined as a sequence of weeks (1st, 2nd, 3rd, or 4th week) of a given month (Table 3).

Although defining the first initial and end dates for each crop calendarin terms of weeks appears to be acceptable from the farmers' practical perspective, it creates some confusion in identifying the exact dates (because a week includes 7 days), which are essential requirements for analyzing the daily time series rainfall data in this study. Thus, to fix the real periods and have reliability in an examination, the starting and the finale dates were taken as the earliest and accomplishment dates for that specific crop calendar, respectively. However, this does not mean that no farmerundertakes key farm activity either initially or later after the defined crop calendar. It should be well known that while LPP, SaMP, and HaTP were defined, some periods of a year became outside of any of the three-cropcalendars (Table 3).

Table 3 | Crop calendar for dominant *Meher* cereal crops in three ACZs of the watershed

ACZs	Midland		Highland		Cold-highland
Crop name	Maize	Teff	Maize	Wheat	Barley
LPP	1^{st}wk Mar - 3^{rd}wk May	1^{st} wk Mar - 4^{th} wk Jun	4^{th} wk Feb - 1^{st} wk May	4^{th} wk Feb - 2^{nd}wk Jun	1^{st} wk Feb – 2^{nd}wk May
SaMP	4^{th}wk May - 2^{nd}wk Oct	1^{st}wk Jul - 3^{rd} wk Oct	2^{nd} wk May - 1^{st} wk Nov	3^{rd} wk Jun - 3^{rd} wk Oct	3^{rd} wk May – 1^{st} wk Oct
HaTP	3^{rd} wk Oct - 2^{nd}wk Nov	4^{th} wk Oct - 3^{rd} wk Nov	2^{nd}wk Nov - 4^{th} wk Nov	4^{th} wk Oct - 2^{nd}wk Nov	2^{nd}wk Oct – 1^{st} wk Nov

Rainfall autocorrelation

All the autocorrelations fell within 5% significance levels, and there was no outward pattern (such as a sequence of positive autocorrelations followed by a sequence of negative autocorrelations). This means the annual rainfall time series for each ACZ did not reveal any significant serial correlations at all lags. The rainfall data were not correlated to each other (Figure 3).

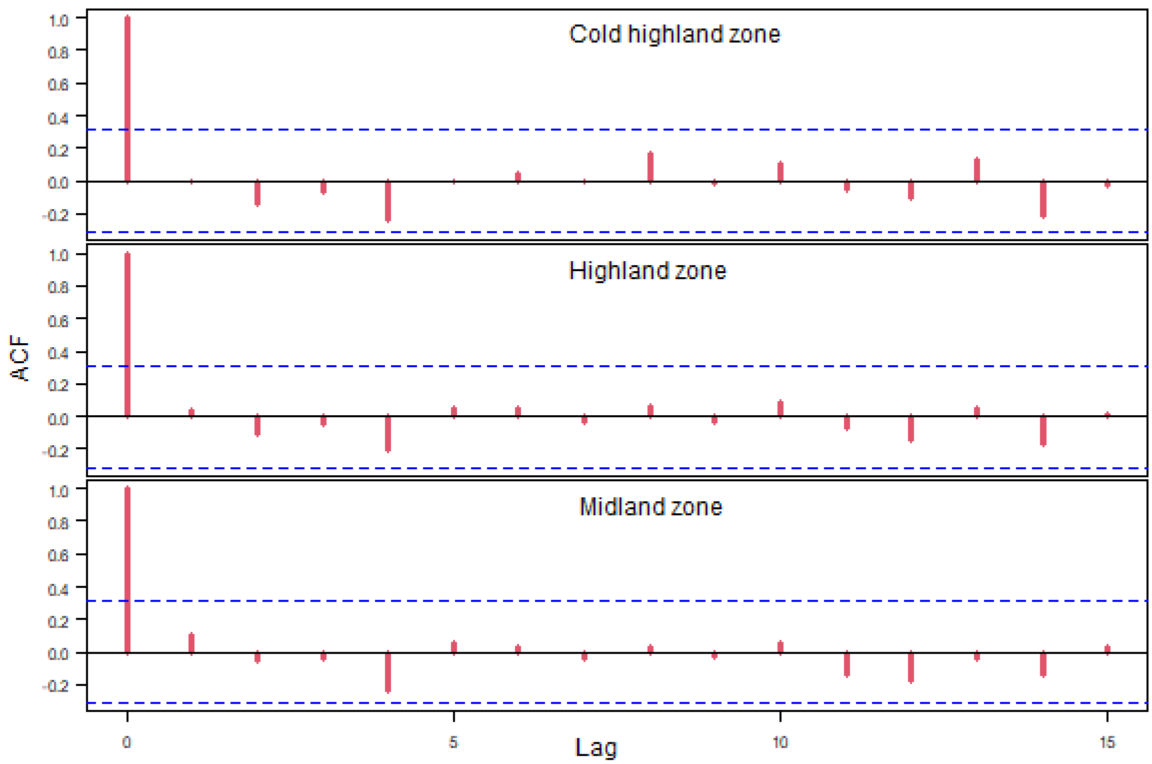

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Figure 3 | The correlation coefficient of the annual rainfall at different lags in three ACZs

These time series were therefore random, meeting the independence distribution criteria. As shown by an earlier studies (Ayalew *et al.*, 2012; Alemu and Bawoke, 2020), the result noted that there was no constant persistence in the observed rainfall series data for the Amhara region of Ethiopia.

However, such non-association was the essence of randomness. In short, adjacent observations did not "correlate" (the areal average annual rainfall data indicated that no dependency and periodicity existed in this time series and suggested areal average annual rainfall quantities are entirely independent of one year to the next). Generally, the examination of the autocorrelation function (ACF) for annual rainfall in all ACZs did not show any significant ongoing correlation by wholly lags at the 5% significance level. Therefore, the analysis of the trends of the rainfall characteristics did not require any further data manipulation; the MK test was applied directly. Results from the serial correlation test, the MK test, and Sen's slope estimator be situated applied to the rainfall data from 1981 to 2019 for the Abiya watershed in all ACZs.

Trends of extreme rainfall indices for the land preparation period

Table (4) presents the long-term means and trends in extreme rainfall indices computed for each crop in each ACZ during the LPP.

Table 4 | Trends in extreme rainfall indices for chosen cereals during LPP in each ACZ

ACZsMidland						
Crop name		Teff			Maize	
Name of indices	Mean	MK	Trend	Mean	MK	Trend
R × 1-day (mm)	28.05	0.65	0.05	20.72	0.45	0.03
R × 5-day (mm)	58.45	0.63	0.09	42.49	0.44	0.11
SDII (mm/day)	7.19	1.32	0.02	6.60	1.36	0.02
R10mm (day)	9.61	**2.01****	0.09	4.38	1.29	0.03
R20mm (day)	2.05	-0.29	0.00	0.79	-0.41	0.00
CDD (day)	82.38	-0.61	-0.06	60.82	0.51	0.34
CWD (day)	38.71	0.62	0.06	20.20	-0.45	-0.03
PRCPTOT(mm)	279.38	1.26	1.39	133.75	0.54	0.34
ACZs			Highland			
Crop name		Wheat			Maize	
Name of indices	Mean	MK	Trend	Mean	MK	Trend
R × 1-day (mm)	26.04	0.12	0.01	21.48	0.34	0.04
R × 5-day (mm)	55.45	0.45	0.10	44	0.29	0.05
SDII (mm/day)	7.09	1.31	0.02	7.09	0.58	0.14
R10mm (day)	8.02	**1.78***	0.10	4.02	0.42	0.00
R20mm (day)	1.62	0.09	0.00	0.76	0.23	0.00
CDD (day)	72.23	-1.19	-0.17	57.18	-0.27	0.00
CWD (day)	34.12	1.13	0.15	17.07	0.21	0.00
PRCPTOT(mm)	245.23	1.52	2.03	119.69	0.17	0.10
ACZs	Cold highland					
Crop name		Barley				
Name of indices	Mean	MK	Trend			
R × 1-day (mm)	26.54	-0.59	-0.07			
R × 5-day (mm)	54.52	0.54	0.17			
SDII (mm/day)	6.72	0.92	0.02			
R10mm (day)	6.3	0.79	0.00			
R20mm (day)	1.2	-0.10	0.00			
CDD (day)	77.59	-0.91	-0.10			
CWD (day)	27.59	0.19	0.00			
PRCPTOT(mm)	184.67	0.74	0.60			

Note * is statistical significance at 0.1, ** is statistical significance at 0.05.

The MK trend tests in the study area showed increasing signals for 75% of the extreme rainfall indices R × 1-day, R × 5-day, SDII, R10mm, CWD, and PRCPTOT and downward signals for the remaining 25% indices R20mm and CDD in the area during the LPP of teff. From all observedextremerainfalltrends in LPP R10mm was only significant in statistical terms at a 5% significance level.

The major 75% increase signals of the extreme rainfall indices R × 1-day, R × 5-day, SDII, R10mm, and PRCPTOT and decrease signals for the remaining 25% R20mm and CWD were observed during the LPP of maize. From all observed increase and decline trends, rainfall extremes were non-significant in statistical terms during the LPP of maize at any level. CWD decreased and divergent trends of CDD. The poor performance of spring rain affects crop production activities during the subsequent main rainy season by influencing the soil moisture and thereby the time of planting long-duration crop varieties such as maize (Gummadi *et al.*, 2018). Additionally, the presence and absence of rainfall greater than1mm were measured using CWD and CDD, respectively. The LPP of maize showed a decreasing trend in CWD and an increasing trend in CDD. According to Worku *et al.* (2019), a decreasing trend in CWD and an increasing trend in CDD suggest an increase in aridity in the area.

The long-term means and trends in extreme rainfall indices computed for wheat during LPP at the highland zone were shown (Table 4). The MK trend tests in the study area show increased signals for 87.5% of the extreme rainfall indices R × 1-day, R × 5-day, SDII, R10mm, R20mm, CWD, and PRCPTOT and downward signals for the remaining 12.5% indices CDD in the area during the LPP. Although from all the observed trends in LPP rainfall extreme, only R10mm was significant in statistical terms at a 10% significance level. As the results of (Table 4), the major 87.5% increase in signals of the extreme rainfall indices R × 1-day, R × 5-day, SDII, R10mm, R20mm, and PRCPTOT and decreased signals for the remaining 12.5% CDD in observed during the LPP of maize. From all observed increase and decline trends, extreme rainfall was non-significant in statistical terms during the LPP of maize. Half of the extreme change was 0.00 days per decade.

The trend analyses did not show systematic patterns among the observed data during the study period in the cold-highland zone for the LPP periods of barley, from the MK trend tests, showed upward signals for 62.5% of the extreme rainfall indices R × 5 day, SDII, R10mm, CWD, and PRCPTOT. Downward signals for 37.5% of the extreme rainfall indices were; R

× 1-day, R20mm, and CDD. The presence and absence of rainfall greater than 1 mm were measured using CWD and CDD, respectively. As shown below, CWD increases and CDD decreases. This suggests that there has been rainfall at LPP of barley, SDII is positive and it was suggested that the daily rainfall has been increasing.

The trends in extreme rainfall indices for LPP also vary among the three ACZs. For example, very heavy rainfall day (R20mm) was decreased in midland and cold-highland zones.On the other hand, it increased in the highland zone. It is understood that the magnitudes and perceived impacts of extreme rainfall indices tend to differ across the three ACZs. Similarly, as indicated by the previous study that was conducted in the wettest part of Ethiopia,a complex trend in the daily rainfall indices was observed (Kebede and Bewket, 2009). Endale *et al.* (2020) also reported inconsistencies and a lack of statistical significance inextreme rainfall indices. For instance, information gotten from FGDsin all ACZs perceived a declining rainfall during LPP has significantly reduced the length of time per season and the time of plowing per day working due to high temperatures.

Trends of extreme rainfall indices for sowing and management period

Table (5) presents the long-term means and trends in extreme rainfall indices computed for each crop in each ACZ during the SaMP.

Table 5 | Trends in extreme rainfall indices for chosen cereals during SaMP in each ACZ

ACZsMidland						
Crop name		Teff			Maize	
Name of indices	Mean	MK	Trend	Mean	MK	Trend
R × 1-day (mm)	37.11	0.21	0.03	38.72	0.00	0.00
R × 5-day (mm)	93.81	0.02	0.00	94	-0.06	-0.01
SDII (mm/day)	10.90	0.21	0.00	10.33	0.16	0.01
R10mm (day)	35.56	-0.36	0.00	39.89	0.66	0.04
R20mm (day)	10.25	0.91	0.00	11.18	0.85	0.04
CDD (day)	35.64	0.01	0.01	52.35	-0.49	-0.04
CWD (day)	77.56	0.04	0.00	93.89	0.67	0.06
PRCPTOT(mm)	845.06	0.02	0.04	968.6	0.83	1.01
ACZs	Highland					
Crop name		Wheat			Maize	
Name of indices	Mean	MK	Trend	Mean	MK	Trend
R × 1-day (mm)	40.27	-0.46	-0.67	40.66	-0.24	-0.03
R × 5-day (mm)	100.79	-0.07	-0.03	100.79	-0.07	-0.03
SDII (mm/day)	11.03	-0.60	-0.01	10.31	-0.77	-0.10

R10mm (day)	40.51	0.61	0.04	45.43	1.22	0.09
R20mm (day)	12.53	-0.52	0.00	13.56	-0.55	0.00
CDD (day)	38.05	-0.69	-0.07	66.02	-1.42	-0.29
CWD (day)	90.17	0.76	0.07	111.38	**1.84***	0.29
PRCPTOT(mm)	994.63	-0.17	-0.21	1146.15	0.68	1.12
ACZs	Cold highland					
Crop name		Barley				
Name of indices	Mean	MK	Trend			
R × 1-day (mm)	42.56	0.41	0.05			
R × 5-day (mm)	105.45	-0.16	-0.04			
SDII (mm/day)	10.76	-0.36	-0.01			
R10mm (day)	46.26	1.03	0.07			
R20mm (day)	14.28	0.05	0.00			
CDD (day)	45.18	-1.34	-0.18			
CWD (day)	104.13	1.27	0.15			
PRCPTOT(mm)	1118.25	0.31	0.53			

Note* is statistical significance at 0.1

Table (5) shows that in the midland, seven out of the eight rainfall indices R×1-day, R× 5-day SDII, R20mm, CDD, CWD, and PRCPTOT showed increasing trends, while the remaining R10mm, revealed decreasing trends for the SaMP of teff. From all the upward and downward signals, there was no significance in statistical terms. The rates of change of some extreme rainfall indices hadno discernible changes (0.00 days/decades). On the other hand, the CDD increased by 0.01 days/decades with a mean of 35.64 days during SaMP of teff. This suggested that long CDD at the critical crop stage has increased over the last three decades. According to Berhane *et al.* (2020),increasing the number of CDD, especially during the main rainy season, could affect crop growth and yield. Additionally, previous studies by Ademe *et al.* (2020) reported that irregularities in the main rainy season rainfall challenged teff planting.The MKs trend tests showed upward signals for 62.5% of the extreme rainfall indices SDII, R20mm, CWD, and PRCPTOT decreased signals for 25% of the extreme rainfall indices R×5-dayand CDD, and no discernible signal for 12.5% of the extreme rainfall indices R × 1-day for SaMP of maize. However, trend analysis shows that there was no significance in statistical terms.

Table (5) also presents the long-term means and trends in extreme rainfall indices for wheat and maize SaMP in highland zones. As is shown, the MK trend tests in the study area showed increased signals for 25% of the extreme rainfall indices R10mm and CWD, and downward signals for the remaining 75% of the indices R × 1-day, R × 5-day, SDII, R20mm, CDD, and PRCPTOT. From all the observed upwards and downwards trends rainfall extremeswere not significant in statistical terms in the area during the SaMP of wheat.In the same tables, the MK result in SaMP of maize is also shown, from observed trend test some of them 37.5% increase signals of the extreme rainfall indices R10mm, CWD, and PRCPTOT and decrease signals for the remaining 62.5% extreme rainfall indices R × 1-day, R × 5-day, SDII, R20mm, and CDD were observed during the SaMP of maize. Only CWD from the observed trends in SaMP rainfall extreme was significant in statistical terms at a 10% significance level. During SaMP of both wheat and maize, the same as other extreme rainfall indices, the trend in SDII is negative. This suggests that the daily rainfall has been declining.

Table (5) also presents the long-term means and trends in extreme rainfall indices for SaMP in cold-highland zones. As it is shown, the MK trend tests in the study area showed increased signals for 62.5% of the extreme rainfall indices R × 1-day, R10mm, CWD, and PRCPTOT, and downward signals for the remaining 37.5 % indices SDII, R×5-day, and CDD in the area during the SaMP of barley. Like other extreme rainfall indices, the trend in SDII is negative during SaMP of barley. This suggested that the daily rainfall has been declining. An increasing trend of R10mm and R20mm were observed among the SaMP of barley. As noted by Worku *et al.* (2019), an increase in these indices suggests potential risks related to flooding and soil erosion around the area. None of the indices from all observed trends in SaMP rainfall extreme were significant in statistical terms.

Most of the rainfall extremes were not significant in statistical terms (except CDD and CWD for the SaMP of maize in the highland zone). As noted by Endale *et al.* (2020),all the observed trends in SaMP rainfall extreme were not significant in statistical terms, but the upward and downward trends could have significant implications for a rain-fed crop production system. The FGDs participants mentioned farming in summer was affected by delayed onset and early termination of rainfall. As pointed outs by farmers, “the rain falls late after sowing time passes and due to early termination of rainfall, the farmlands get dry and crops do not grow very well and in all ACZs perceived that impacts of heavy rainfall and long CDD at critical crop stage have increased over the last three decades years. Conversely, teff needs buddy character during the SaMPin nature but the long CDD may have undesirable damage. Their perceptions were consistent with the recorded trends in the long CDD at the midland zone for SaMP of teff and heavy rainfall partially consistent with the recorded trends at three ACZs.

In the highland and cold-highland area, the SDII show a negative trend. As noted byMohammed *et al.* (2018)the decreasing trends of SDII indicate that agricultural production was at risk. For example, the consequence of CDD with the same length may be more severe if it occurs at the early growing period of crops than at the later stage (Yu *et al.*, 2018). Former work by Chabala *et al.* (2013) also confirms that though a CDD of 4 in 30-days after sowing might be understood to be less significant, it could still be dangerous to crop growth since its impact is cumulative. Generally, the occurrence of long-lasting dry periods during critical growing and development stages can have serious influences on crop yield (Yu *et al.*, 2018).

Megersa *et al.* (2020) reported that rainfall variability directly or indirectly affects agricultural production by influencing the growth and development of crops by aggravating the frequency and distribution of adverse weather conditions, reducing water aggravating the frequency, and distribution of adverse weather conditions, reducing water supplies and enhancing the severity of soil erosion. While, rainfall variability has always been a major challenge for Ethiopian agriculture. farmers planning flexible planting dates based on the onset time of the rainfall season, however, crop failure due to false starts of the rainfall season is may be a common risk (Kassie *et al.*, 2013).

The major problem as far as rainfall distribution was concerned found by FGDs in the watershed was not the amount but rather the variability and change in the onset and cessation periods. The rain onsets late recently the last one weeks of June and end up before September. Additionally, the FGDs participant mentioned the rainfall for the *Meher* season has been decreasing (expected to onset in June) and September (the flowering stage of the *Meher* crops). On the other hand, rainfall during September is essential because the crops for the duration of this time are at the flowering or ripening stage and require more water for maturation.

Trends of extreme rainfall indices for harvesting and threshing period

Table (6) presents the long-term means and trends in extreme rainfall indices computed for each crop in each ACZ during the HaTP.

Table 6 | Trends in extreme rainfall indices for chosen cereals during HaTP in each ACZ

ACZsMidland						
Crop name		Teff			Maize	
Name of indices	Mean	MK	Trend	Mean	MK	Trend
R × 1-day (mm)	12.14	1.21	0.13	15.32	0.60	0.09
R × 5-day (mm)	31	0.47	0.17	41.53	0.35	0.2
SDII (mm/day)	5.54	0.57	0.02	7.4	-0.18	-0.09
R10mm (day)	1.34	1.23	0.00	1.97	0.76	0.00
R20mm (day)	0.18	0.39	0.00	0.51	0.20	0.00
CDD (day)	24.44	-1.40	-0.06	17.56	-1.11	-0.07
CWD (day)	6.59	1.46	0.07	6.48	1.28	0.07
PRCPTOT(mm)	39.15	1.16	0.42	51.67	0.94	0.4
ACZs	Highland					
Crop name		Wheat			Maize	
Name of indices	Mean	MK	Trend	Mean	MK	Trend
R × 1-day (mm)	10.96	1.08	0.11	8.73	0.52	0.03
R × 5-day (mm)	30.68	0.44	0.94	20.5	0.87	0.14
SDII (mm/day)	5	0.00	0.00	4.38	0.11	0.00
R10mm (day)	1.23	0.65	0.00	0.51	-1.17	0.00
R20mm (day)	0.15	-0.12	0.00	0.00	0.00	0.00
CDD (day)	23.85	-1.55	-0.09	24.87	-1.30	-0.05
CWD (day)	7.25	**1.66***	0.1	5.28	1.32	0.06
PRCPTOT(mm)	39.55	1.23	0.42	23.38	0.97	0.22
ACZs	Cold highland					
Crop name		Barley				
Name of indices	Mean	MK	Trend			
R × 1-day (mm)	18.49	0.56	0.08			
R × 5-day (mm)	47.129	-0.48	-0.17			
SDII (mm/day)	7.55	0.31	0.01			
R10mm (day)	2.41	0.21	0.00			
R20mm (day)	0.67	0.05	0.00			
CDD (day)	15.87	-0.88	-0.05			
CWD (day)	98.79	1.02	0.07			
PRCPTOT(mm)	68.47	0.28	0.17			

Note* is statistical significance at 0.1

The trend analyses did not show systematic patterns among the recording data during the study period at the midland zone for the HaTP periods of both teff and maize. The MK trend tests showed upward signals for 87.5% of the extreme rainfall indices R × 1-day, R × 5-day, SDII, R10mm, R20mm, CWD, and PRCPTOT, downward signals for 12.5% indices CCD for teff. Unlike other extreme rainfall indices, the trend in CCD was negative during the HaTP of teff. This suggested that the daily rainfall has been increasing. The MK trend tests showed upward signals for 75% of the extreme rainfall indices R × 1-day, R × 5-day, R10mm, R20mm, CWD, and PRCPTOT, and downward signals for 25% indices SDII and CCD during HaTP of maize.

The trend signals for 62.5% of the indices R × 1-day, R × 5-day, SDII, R10mm, CWD, and PRCPTOT were increasing and 25% of the indices R20mm and CDD were decreasing and 12.5% of the indices SDII was no discernible signal during the HaTP of wheat. The CWD has increased statistically significantly at a5% significance level. Long consecutive wet days (CWD) during the harvesting period wereparticularly the main to adversely affecting crop production. Additionally, most of the extreme increased and convergent signals of CDD. This suggests there was rainfall during the HaTP of wheat in the highland area. Results in the same table show the trend signals for 62.5% of the indices R × 1-day, R × 5-day, SDII, CWD, and PRCPTOT were increasing and 25% of the indices R20mm and CDD were decreasing, and 12.5% of the indices R20mm was no discernible signal during the harvesting times of maize in the highland area. However, there were no statistically significant trend tests for all upward and downward signals for both crop types. All of the extreme rainfall indices observed in trend tests were not statistically significant during the HaTP of maize.

Table (6) also presents the long-term means and trends in extreme rainfall indices for the HaTP of barley in the cold highland. The trend signals for 75% of the indices R × 1-day, SDII, R10mm, R20mm, CWD, and PRCPTOT were increasing and 25% of the indices Rx5-day and CDD were decreasing during the harvesting times of barley in the area, however, there were no statistically significant trend tests for all upward and downward signals for barley crop types. Most of the daily rainfall extreme increase and on the other hand decrease CDD, this shows there was rainfall during the HaTP of barley.

The extreme rainfall indices analysis showed an increase in the most extreme rainfall indices in all ACZs. The presence and absence of rainfall greater than 1 mm were measured using CWD and CDD, respectively. An increasing trend of CWD was significant in the highland zone. CDD was insignificantly decreasing in all ACZs. An increasing trend of R10mm and R20mm were observed in all ACZs except in the highland (maize) during HaTP. It was also shown by Worku *et al.* (2019) that an increase in the indices suggests potential risks related to flooding and soil erosion around the area.

The increased and decreased signals in HaTP rainfall indices found for different ACZs have different and significant implications for the rain-fed crop production system. Exceptingthe decreasing trend, all the observed increasing trends in HaTP rainfall indices at midland, highland, and cold-highland zone indicate the deteriorating process of climatic conditions for *Meher* crops at the maturity stage and harvesting and threshing operations in all ACZs. The extreme rainfall indices analysis shows an increase in most extreme rainfall indices in the entire watershed during HaTP. This trend in rainfall extreme substantiates that the rainfall trend has not been stable in the Abiya watershed. This suggests that extreme rainfall events may pose damage to socio-economic activities and ecosystems.

Evidence gained from FGDs in all ACZs confirmed that happenings of extreme rainfalls such as long CWD rainfalls during HaTP have serious consequences on crop production; harm dried crops physically, dampen and germinate grains before and after harvesting, increase labor requirements and develop stress on farmers. Their perception was consistent with the recorded trends in the rainfall indices in all ACZs. Even normal rain is harmful for the harvesting period. Earlier studies by (Asfaw *et al.*, 2018) reported that rainfall occurring during the harvesting period could cause damage to crops and delay harvesting. A study by Deressa and Hassan (2009) in Ethiopia also estimated a reduction in net revenue of crops per hectare with an increasing level of rainfall during the harvesting season. Harvesting time may cause shattering of crop grains, pre-harvest seed germination, and disturbing harvesting operations. Due to the erratic rainfall distribution, up to 100% of crop losses were recorded in various parts of the West ArsiAdministrative Zone of the Oromia Region in different crop growing years (Teklewold *et al.*, 2013).

CONCLUSIONS

The analysis of daily extreme rainfall indices for the *Meher* season cereal crop calendarshowedan increasing trendin the three ACZs of the watershed. Yet only a few of them were statistically significant. Most of the increasing trends for LPP, SaMP, and HaTP were witnessed in the highland, midland, and all ACZs, respectively. In contrast, some of the decreasing trends in extreme rainfall indices for LPP,SaMP, and HaTPwere recorded in the cold-highland, highland, and all ACZs zone.Although the MK's trend tests were not statistically significant for most of the extreme rainfall indices, the upward and downward signals were observed to have negative consequences for rain-fed-based crop production. The level of daily extreme rainfall indicesvariesspatiallyand among cereal crops.The study suggests applying appropriate soil and water conservation measures together withadapting suitable crop varieties and drought-tolerance crops, andan accurate early warning system.

A preprint in thesis format has previously been published (Azene, E., 2022).

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DATA AVAILABILITY STATEMENT

All relevant rainfall data are available online. A record of daily rainfall data for this study was taken from 50 sample grids points (each representing areas of 5 × 5 km) to study from the CHIRPS dataset, which was accessible online at http://climexp.knmi.nl/select.cgi?field=chirps_20_25.

CONFLICT OF INTEREST STATEMENT

The authors declare no conflict of interest.

REFERENCES

Ademe, D., Ziatchik, B. F., Tesfaye, K., Simane, B., Alemayehu, G. & Adgo, E. 2020 Climate trends and variability at adaptation scale: Patterns and perceptions in an agricultural region of the Ethiopian Highlands. *Weather and Climate Extremes,* **29,** 100263.

Alemayehu, A. & Bewket, W. 2017 Determinants of smallholder farmers' choice of coping and adaptation strategies to climate change and variability in the central highlands of Ethiopia. *Environmental Development,* **24,** 77-85.

Alemu, M. M. & Bawoke, G. T. 2020 Analysis of spatial variability and temporal trends of rainfall in Amhara region, Ethiopia. *Journal of Water and Climate Change,* **11,** 1505-1520.

Asfaw, A., Simane, B., Hassen, A. & Bantider, A. 2018 Variability and time series trend analysis of rainfall and temperature in north-central Ethiopia: A case study in Woleka sub-basin. *Weather and climate extremes,* **19,** 29-41.

Ayalew, D., Tesfaye, K., Mamo, G., Yitaferu, B. & Bayu, W. 2012 Variability of rainfall and its current trend in Amhara region, Ethiopia. *African Journal of Agricultural Research,* **7,** 1475-1486.

Bayable, G., Amare, G., Alemu, G. & Gashaw, T. 2021 Spatiotemporal variability and trends of rainfall and its association with Pacific Ocean Sea surface temperature in West Harerge Zone, Eastern Ethiopia. *Environmental Systems Research,* **10,** 1-21.

Berhane, A., Hadgu, G., Worku, W. & Abrha, B. 2020 Trends in extreme temperature and rainfall indices in the semi-arid areas of Western Tigray, Ethiopia. *Environmental Systems Research,* **9,** 1-20.

BoFED, A. R. 2014. Population Size of the Amhara Region by age group. Bahirdar: Amhara Regional State Bureau of Finance and Economic Development.

Chabala, L. M., Kuntashula, E. & Kaluba, P. 2013 Characterization of temporal changes in rainfall, temperature, flooding hazard and dry spells over Zambia. *Universal Journal of Agricultural Research,* **1,** 134-144.

Chattopadhyay, S. & Edwards, D. R. 2016 Long-term trend analysis of precipitation and air temperature for Kentucky, United States. *Climate,* **4,** 10.

Deressa, T. T. & Hassan, R. M. 2009 Economic impact of climate change on crop production in Ethiopia: Evidence from cross-section measures. *Journal of African economies,* **18,** 529-554.

Dinku, T., Funk, C., Peterson, P., Maidment, R., Tadesse, T., Gadain, H. & Ceccato, P. J. Q. J. o. t. R. M. S. 2018 Validation of the CHIRPS satellite rainfall estimates over eastern Africa. **144,** 292-312.

Dinku, T., Hailemariam, K., Maidment, R., Tarnavsky, E. & Connor, S. 2014 Combined use of satellite estimates and rain gauge observations to generate high-quality historical rainfall time series over Ethiopia. *International Journal of Climatology,* **34,** 2489-2504.

Endale, B. W., Simphiwe, E. M. & Yimer, A. A. 2020 Trends in climate extremes at local farming calendar timescale: evidence from Merti District, Ethiopia. *Modeling Earth Systems and Environment*, 1-11.

Azene, E. (2022). Rainfall variability and its impact on crop calendar among the agro-climatic zones of Abiya watershed, northwest Ethiopia. Bahir Dar university, Ethiopia, Thesis Report.

Feng, G., Cobb, S., Abdo, Z., Fisher, D. K., Ouyang, Y., Adeli, A. & Jenkins, J. N. 2016 Trend analysis and forecast of precipitation, reference evapotranspiration, and rainfall deficit in the Blackland Prairie of Eastern Mississippi. *Journal of Applied Meteorology and Climatology,* **55,** 1425-1439.

Fenta, A. A., Yasuda, H., Shimizu, K., Ibaraki, Y., Haregeweyn, N., Kawai, T., Belay, A. S., Sultan, D. & Ebabu, K. 2018 Evaluation of satellite rainfall estimates over the Lake Tana basin at the source region of the Blue Nile River. *Atmospheric Research,* **212,** 43-53.

Fiwa, L., Vanuytrecht, E., Wiyo, K. A. & Raes, D. 2014 Effect of rainfall variability on the length of the crop growing period over the past three decades in central Malawi. *Climate Research,* **62,** 45-58.

Geremew, G. M., Mini, S. & Abegaz, A. 2020 Spatiotemporal variability and trends in rainfall extremes in Enebsie Sar Midir district, northwest Ethiopia. *Modeling Earth Systems and Environment,* **6,** 1177-1187.

Gummadi, S., Rao, K., Seid, J., Legesse, G., Kadiyala, M., Takele, R., Amede, T. & Whitbread, A. 2018 Spatio-temporal variability and trends of precipitation and extreme rainfall events in Ethiopia in 1980–2010. *Theoretical and Applied Climatology,* **134,** 1315-1328.

Hoegh-Guldberg, O., Jacob, D., Bindi, M., Brown, S., Camilloni, I., Diedhiou, A., Djalante, R., Ebi, K., Engelbrecht, F. & Guiot, J. 2018 Impacts of 1.5 C global warming on natural and human systems. *Global warming of 1.5 C. An IPCC Special Report*.

Jain, S. K. & Kumar, V. 2012 Trend analysis of rainfall and temperature data for India. *Current Science*, 37-49.

Kassie, B. T., Hengsdijk, H., Rötter, R., Kahiluoto, H., Asseng, S. & Van Ittersum, M. 2013 Adapting to climate variability and change: experiences from cereal-based farming in the Central Rift and Kobo Valleys, Ethiopia. *Environmental Management,* **52,** 1115-1131.

Kebede, G. & Bewket, W. 2009 Variations in rainfall and extreme event indices in the wettest part of Ethiopia. *SINET: Ethiopian Journal of Science,* **32,** 129-140.

Lemma, E., Upadhyaya, S. & Ramsankaran, R. 2019 Investigating the performance of satellite and reanalysis rainfall products at monthly timescales across different rainfall regimes of Ethiopia. *International Journal of Remote Sensing,* **40,** 4019-4042.

Libanda, B. 2020 Multi-model synthesis of future extreme temperature indices over Zambia. *Modeling Earth Systems and Environment***,** 1-15.

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

Lyon, B. 2014 Seasonal drought in the Greater Horn of Africa and its recent increase during the March-May long rains. *Journal of Climate,* **27,** 7953-7975.

Mandale, V., Mahale, D., Nandgude, S., Gharde, K. & Thokal, R. 2017 Spatio-temporal rainfall trends in Konkan region of Maharashtra State. *Advanced Agricultural Research & Technology Journal,* **1,** 61-69.

Megersa, G., Tesfaye, K., Getnet, M., Tana, T., Jaleta, M. & Lakew, B. 2020 Rainfall Variability and its Implications for Wheat and Barley Production in Central Ethiopia. **7,** 89-111.

Mika, J. 2013 Changes in weather and climate extremes: phenomenology and empirical approaches. *Climatic Change,* **121,** 15-26.

MoA 2000 Agroecological zonations of Ethiopia. *Addis Abeba Ethiopia.*

Mohammed, Y., Yimer, F., Tadesse, M. & Tesfaye, K. 2018 Variability and trends of rainfall extreme events in northeast highlands of Ethiopia. *Int J Hydro,* **2,** 594-605.

Ngongondo, C., Xu, C.-Y., Gottschalk, L. & Alemaw, B. 2011 Evaluation of spatial and temporal characteristics of rainfall in Malawi: a case of the data-scarce region. *Theoretical and applied climatology,* **106,** 79-93.

Omambia, A. N., Shemsanga, C. & Hernandez, I. A. S. 2017 Climate change impacts, vulnerability, and adaptation in East Africa (EA) and South America (SA). *Handbook* *of climate change mitigation and adaptation. Springer International Publishing Switzerland*, 749-799.

Omondi, P. A. o., Awange, J. L., Forootan, E., Ogallo, L. A., Barakiza, R., Girmaw, G. B., Fesseha, I., Kululetera, V., Kilembe, C. & Mbati, M. M. 2014 Changes in temperature and precipitation extremes over the Greater Horn of Africa region from 1961 to 2010. *International Journal of Climatology,* **34,** 1262-1277.

Poudel, S. & Shaw, R. 2016 The relationships between climate variability and crop yield in a mountainous environment: A case study in Lamjung District, Nepal. *Climate,* **4,** 13.

Stern, R., Rijks, D., Dale, I. & Knock, J. 2006 INSTAT climatic guide. *Reading (UK): University of Reading*.

Suryabhagavan, K. 2017 GIS-based climate variability and drought characterization in Ethiopia over three decades. *Weather and climate extremes,* **15,** 11-23.

Taye, M., Sahlu, D., Zaitchik, B. F. & Neka, M. 2020 Evaluation of Satellite Rainfall Estimates for Meteorological Drought Analysis over the Upper Blue Nile Basin, Ethiopia. *Geosciences,* **10,** 352.

Teklewold, A., Mamo, G. & Admassu, H. 2013 2. Impacts of climate change on crop production in Ethiopia. *Climate Change Vulnerability and Risk Assessment of Agriculture and Food Security in Ethiopia*, 13.

Tierney, J. E., Smerdon, J. E., Anchukaitis, K. J. & Seager, R. 2013 Multidecadal variability in East African hydroclimate controlled by the Indian Ocean. *Nature,* **493,** 389-392.

Von Storch, H. 1999. Misuses of statistical analysis in climate research. *Analysis of climate variability.* Springer.

WMO 2009 Guidelines on analysis of extremes in a changing climate in support of informed decisions for adaptation. Geneva Switzerland.

Worku, G., Teferi, E., Bantider, A. & Dile, Y. T. 2019 Observed changes in extremes of daily rainfall and temperature in Jemma Sub-Basin, Upper Blue Nile Basin, Ethiopia. *Theoretical and Applied Climatology,* **135,** 839-854.

Wu, C., Huang, G., Yu, H., Chen, Z. & Ma, J. 2014 Spatial and temporal distributions of trends in climate extremes of the Feilaixia catchment in the upstream area of the Beijiang River Basin, South China. *International Journal of Climatology,* **34,** 3161-3178.

Yang, W., Seager, R., Cane, M. A. & Lyon, B. 2014 The East African long rains in observations and models. *Journal of Climate,* **27,** 7185-7202.

Yu, H., Zhang, Q., Sun, P. & Song, C. 2018 Impact of droughts on winter wheat yield in different growth stages during 2001–2016 in Eastern China. *International Journal of Disaster Risk Science,* **9,** 376-391.