



# Spatiotemporal variability and trend analysis of rainfall in Beshilo sub-basin, Upper Blue Nile (Abbay) Basin of Ethiopia

Jemal Ali Mohammed<sup>1</sup> · Zinet Alye Yimam<sup>1</sup>

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## Abstract

Rainfall variability is a common characteristic in Ethiopia that affects socioeconomic and ecological systems. In this study, we estimated the spatiotemporal variability and trend of rainfall from 1981 to 2019 in the Beshilo sub-basin of the Upper Blue Nile Basin (UBNB) using CHIRPS satellite rainfall estimates. The coefficient of variation (CV) and standardized anomaly index (SAI) were used to assess rainfall variability. The Mann-Kendall (MK) trend test and Sen's slope estimator were also employed to analyze the trend and extent of rainfall changes, respectively. The results showed that different rainfall events occurred in the catchment area, particularly on monthly and seasonal time scales. The annual rainfall CV ranges from 13.5–18.5% while the seasonal rainfall CV ranges from 15–40.6%, 36.5–85.7%, and 19–100.3% for the Kiremt (June–September), Belg (March–May), and Bega (October–February) seasons, respectively. The standardized anomaly index (SAI) also indicates the presence of moderate rainfall variability between the years with negative and positive anomalies in 53.84% and 46.15% of the years analyzed, respectively. On a seasonal basis, the negative SAI of rainfall is 48.7%, 53.84%, and 51.28% in the Kiremt, Belg, and Bega seasons, respectively. The trends of annual and Kiremt rainfall showed an increasing trend and decreasing trends in Belg and Bega rainfall were analyzed. The rising and declining trend for Kiremt and Bega rainfall was statistically significant ( $\alpha = 0.05$ ). Monthly, rainfall trends increased in all months except in February, March, April, and December. These results, therefore, highlight the need to plan and implement effective strategies for adapting to rainfall variability.

**Keywords** CHIRPS · MK trend test · Sens' slope · Rainfall variability · Beshilo sub-basin

## Introduction

In the recent decades, there have been rapid changes and fluctuations in the earth's climate system that have never occurred over an extended period of time (Ramanathan 1988; Boisvenue & Running 2006; IPCC 2013; Pepin et al. 2015; Ummenhofer and Meehl 2017; Wang et al. 2018). As a result of the drastic climate change and variability, a multitude of effects have been seen on society, the environment, and the economy worldwide (Thornton et al. 2014; Frei et al. 2015; Birkmann and Mechler 2015; Weldegerima et al. 2018; IPCC 2013). Rainfall is among the most influential

weather and climate variables. It affects the spatial and temporal distribution of water in agricultural production, energy production, food production, and all water resources infrastructure across the globe (Demekie et al. 2011; Bello et al. 2012; Weldegerima et al. 2018; Ayehu et al. 2018). More than 85% of the African population depends on resources that are affected by climatic fluctuations and rain-fed agriculture (Diro et al. 2011; Lalego et al. 2019; Schilling et al. 2020). This makes them particularly vulnerable to risks arising from the variability of rainfall (Anyah and Qiu 2012).

Rainfall patterns in East Africa exhibit large seasonal and interannual fluctuations that contribute to extreme weather events such as droughts and floods (Mekasha and Duncan 2013; Viste and Sorteberg 2013; Omondi et al. 2014). In Ethiopia, rainfall varies widely due to seasonal changes and complex topography as well (Mekasha and Duncan 2013; Asfaw et al. 2018; Gebrechorkos et al. 2019). Variability in the spatial distribution of rainfall can be described by the seasonal rainfall cycle, the amount of rainfall, the beginning

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✉ Jemal Ali Mohammed  
Jemalali344@gmail.com

<sup>1</sup> Department of Forestry, College of Agriculture and Natural Resources, Mekdela Amba University, Tuluawlia, Ethiopia

and ending times, and the length of the vegetative period (Segele and Lamb 2005). It is also possible for rainfall to vary over time from days to decades in terms of the direction and extent of rainfall trends across regions and seasons (Viste and Sorteberg 2013; Worku et al. 2019; Dawit et al. 2019). As a result of climate variability, climate extremes such as droughts or floods have resulted in a significant impact on millions of poor farmers and natural ecosystems, as well as people's socioeconomic status (Worku et al. 2019; Tessema and Simane 2020). Hence, the increased capacity of consistent and adequate seasonal rainfall trend analysis and rainfall forecasting is essential to addressing future rain-related disasters (Diro et al. 2011).

Therefore, it is crucial to study the spatiotemporal dynamics of increased rainfall variability, in order to develop strategies and agricultural practices for adaptation (Asfaw et al. 2018; Lalego et al. 2019; IPCC 2021). For this, we need high-frequency in situ observations in both space and time that are as comprehensive as possible. Several studies have identified poor data quality, data discontinuities, a lack of evenly distributed stations, availability, and accessibility to be the most fundamental obstacles in developing countries in general and Ethiopia in particular (Katsanos et al. 2016; Kimani et al. 2017; Fenta et al. 2018). These are also the limitations in the Beshilo sub-basin where this study was conducted. Nevertheless, advances in satellite-based rainfall data sets have been widely used as an alternative to long-term station observations to better characterize the spatial footprints associated with climate change (Ayehu et al. 2018; Dinku et al. 2018; Fenta et al. 2018; Cattani et al. 2018; Alemu and Bawoke 2020).

Several studies have been carried out in Ethiopia (e.g., Degefu and Bewket 2014; Gummadi et al. 2018; Mohammed et al. 2018; Weldegerima et al. 2018; Gedefaw et al. 2019; Dawit et al. 2019; Abegaz 2020; Geremew et al. 2020; Ademe et al. 2020) to assess rainfall variability and trends. According to studies cited above, rainfall in different Ethiopian agroecological zones exhibits various trends and variations. In addition, most of the previous studies have been limited to data from a few meteorological stations. A study of the temporal and spatial variability of rainfall in Beshilo sub-basin, which is often affected by climate-related disasters, does not exist. According to the abovementioned studies, a more comprehensive study of spatial and temporal variability and trend of rainfall at the local level is needed by analyzing high-resolution geospatial data. For this purpose, Climate Hazards Group InfraRed Rainfalls with Stations (CHIRPS) has provided long-term, high-resolution data sets that can be used to examine rainfall variability and trends. The main objective of this study was, therefore, to assess the spatial distribution and temporal trends of rainfall in the Beshilo sub-basin of the UBNB, using CHIRPS satellite rainfall estimates. Findings from this study will be

crucial for the development of effective strategies for adapting to and coping with climate change. It will also have broad implications for many other regions of the world with agroecologies similar to those in the Beshilo sub-basin.

## Materials and methods

### Descriptions of the study area

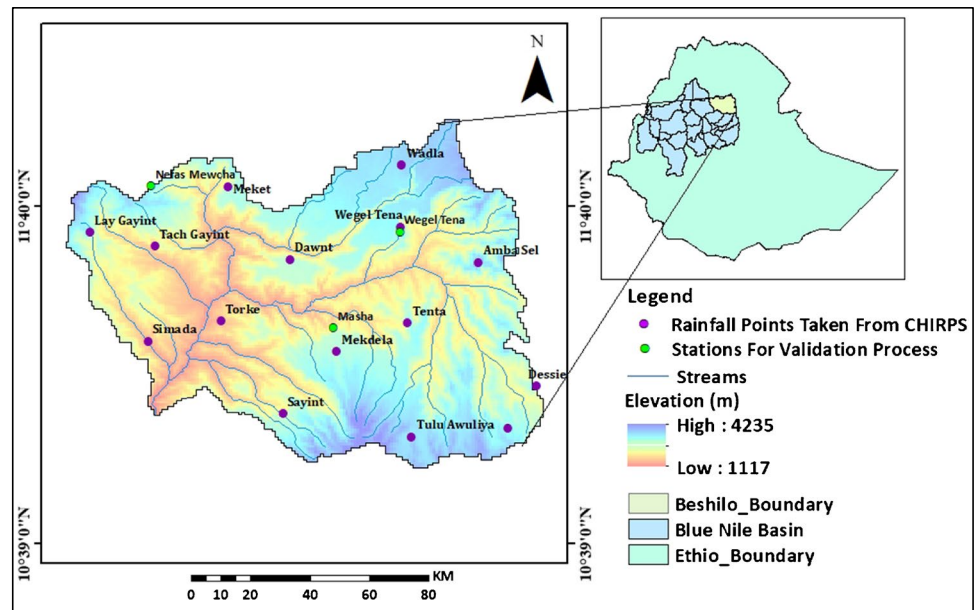
The Beshilo basin is one of the sub-basins of the UBNB, locally known as Abbay in Ethiopia. It has an estimated area of 13,243 km<sup>2</sup> and extends between 38° 58' 8.760" E and 11° 20' 57.954" N. Its elevation ranges from 1117 to 4235 m above sea level (Fig. 1). A region of moist and sub-moist middle highlands can be found in the basin, whereas the afro-alpine to sub-afro-alpine highlands can be cold to very cold. The lowlands in the southeastern parts of the basin are hot to warm humid lowlands (Yilma and Awulachew 2009). There are three rainy seasons in this area, locally called *Kiremt*, *Belg*, and the *Bega*. The main rainy season is *Kiremt*, which extends from June to September. *Belg* is a short rainy season from March to May, while the *Bega* is a dry season from October to February. Rainfall in the basin ranges from 825 to 1470 mm on average every year. The annual maximum and minimum temperature in the sub-basin fluctuates between 13 to 30 °C and −1 to 15 °C. The majority of the sub-basin's land is used for cultivation, with only a few parts used for pasture (Yilma and Awulachew 2009; Ahmad et al. 2020).

### Data types and sources

To conduct this study, we used high-resolution satellite rainfall data from remote sensing satellite estimates. Most of the rainfall data from meteorological station observations are inadequate in the study area due to sparse or non-existent station networks (Alemayehu and Bewket 2017a; Bayissa et al. 2017; Asfaw et al. 2018; Alemu and Bawoke 2020). In addition, rainfall data from in situ meteorological stations included recordings over short periods and a large percentage of missing records to aid in trend analysis.

In this case, the satellite rainfall data from the Climate Hazards Group Infrared Rainfall with Stations (CHIRPS) (<https://data.chc.ucsb.edu/products/CHIRPS-2.0/>) is a very reliable source of rainfall data (Bayable et al. 2021; Dinku et al. 2018; Belay et al. 2019). CHIRPS is a quasi-global dataset (covering the range between 50° N and 50° S) available from 1981 to the present day with a spatial resolution of 0.05° (~5.3 km) and created using multiple data sources (Funk et al. 2015). The data product CHIRPS is developed by the U.S. Geological Survey (USGS) and the Climate Hazards Group (CHG) of the University of California (Knapp et al. 2011; Funk et al. 2015). We chose this newly developed satellite rainfall product

**Fig. 1** Map of the study area and the climate stations used



because of its relatively high spatial resolution over long time series and the inexpensive information about rainfall on different time scales.

The daily observed rainfall station data for Masha, Dessie, Nefas Mewcha, and Wegel Tena were obtained from the National Meteorological Agency (NMA) of Ethiopia to validate the satellite-derived rainfall products in the study region (Table 1). The missing data values were filled in using the Multivariate Imputation by Chained Equations (MICE) algorithm (Buuren 2014) that completes missing values at a single station, using the complete observed values of all stations examined as predictors. The rainfall data of all selected stations were subjected to quality control and homogeneity test of their series with the software RCLimDex to identify questionable data sets in the weather data sets (Zhang et al. 2004). Once these measures were undertaken, annual, monthly, and seasonal data were calculated from the daily rainfall records for each station. This was done to assess the accuracy of the CHIRPS satellite rainfall product.

**Evaluation of CHIRPS rainfall data**

Advances in satellite observation are becoming an ever-increasing source of up-to-date, repetitive, and inexpensive

rainfall data on various time scales. However, uncertainties due to spatiotemporal sampling errors, errors in algorithms, and satellite instruments can affect the accuracy and result from a significant error in satellite-based rainfall patterns and variability studies (Kimani et al. 2017; Dinku et al. 2018; Fanta et al., 2018; Belay et al. 2019; Alemu and Bawoke 2020; Bayable et al. 2021). Thus, the reliability of the satellite-derived rainfall products must be evaluated with the corresponding rain gauge data before using them for the planned application (Dinku et al. 2018; Fenta et al. 2018; Belay et al. 2019). The performance of different satellite-derived rainfall estimates has been evaluated across Africa including in different parts of Ethiopia (Bayissa et al. 2017; Kimani et al. 2017; Ayehu et al. 2018; Dinku et al. 2018; Fenta et al. 2018; Bayable et al. 2021) and their results showed that the CHIRPS estimates are significantly better than most other long-term satellite rainfall products. However, further validation work needs to be carried out for the relatively recently developed CHIRPS rainfall product on different spatial and temporal scales over Ethiopia (Ayehu et al. 2018).

In this study, we assessed the performance of CHIRPS satellite rainfall estimates on monthly, seasonal, and annual timescales based on four rain gauge observations.

**Table 1** Properties of in situ meteorological stations and percentage of the missing value

No.	Stations	Geographical coordinates		Elevation	Period of record	Missing data (%)
		Latitude (°)	Longitude (°)			
1	Masha	39.02	11.3	1792	2008–2018	4.68
2	Dessie	40.66	11.12	2553	2007–2019	9.36
3	Nefas Mewcha	38.468	11.73	1800	1998–2015	5.53
4	Wegel Tena	39.22	11.59	1973	1998–2015	13.43

We downloaded CHIRPS rainfall estimates in a raster format and used the Python 3.8.5 (Van Rossum and Drake 2001) software to retrieve the desired point values at a spatial resolution of 0.05° latitude-longitude. Additionally, the point values of the CHIRPS rainfall estimates were extracted at rain gauge locations in order to validate the CHIRPS rainfall estimates. The comparison between the extracted CHIRPS satellite rainfall estimates and the ground rainfall observation data was made with various statistical measures (Bayissa et al. 2017; Kimani et al. 2017; Ayehu et al. 2018; Dinku et al. 2018; Fenta et al. 2018; Alemu and Bawoke 2020; Bayable et al. 2021). The validation statistics used here are as follows:

i Pearson coefficient

The Pearson correlation coefficient ( $r$ ) is used to measure the goodness of fit and the linear relationship between CHIRPS and rainfall data from meteorological stations (Alemu and Bawoke 2020). Its value ranges from a negative one to a positive one, with a positive one indicating the perfect score. The Pearson correlation coefficient ( $r$ ) was calculated using the formula:

$$r = \frac{\sum_{i=1}^n (O_i - \bar{O})(P_i - \bar{P})}{\sqrt{\sum_{i=1}^n (O_i - \bar{O})^2 \sum_{i=1}^n (P_i - \bar{P})^2}} \quad (1)$$

where  $O_i$  is the observation value and  $P_i$  is the forecast value and  $\bar{O}$  is average of observation values and  $\bar{P}$  is average of forecast values.

ii Nash Sutcliffe Efficiency coefficient

The Nash-Sutcliffe coefficient of efficiency (NSE) was used to show the relative magnitude of the variance in residuals compared to the variance in observed rainfall values (Nash and Sutcliffe 1970). The value ranges from  $-\infty$  to 1, with higher values indicating a better match between CHIRPS satellite rainfall data and meteorological station data. Negative NSE values indicate that the meteorological station is a better estimate than the CHIRPS rainfall products; 0 indicates that the meteorological station is as good as the CHIRPS rainfall products. It was calculated using the formula:

$$NSE = 1 - \frac{\sum_{i=1}^n (O_i - P_i)^2}{\sum_{i=1}^n (O_i - \bar{P})^2} \quad (2)$$

where  $O_i$  is the observation value and  $P_i$  is the forecast value and  $\bar{O}$  is average of observation values and  $\bar{P}$  is average of forecast values.

iii Root mean square error

The root mean square error (RMSE) was used to measure the difference between values predicted by

CHIRPS satellite rainfall data and meteorological station data. These individual differences are also known as residuals, and the root mean square error serves to aggregate them into a single measure of predictive power. Root mean square error measures how much error there is between CHIRPS satellite rainfall data and station data sets. Its value ranges from 0 to  $\infty$ , and the maximum value is zero. It was calculated using the equation:

$$RMSE = \frac{\sqrt{\sum_{i=1}^n (O_i - P_i)^2}}{n} \quad (3)$$

where  $O_i$  is the meteorological gauge rainfall value and  $P_i$  is the CHIRPS rainfall value.

iv Mean absolute error

Mean absolute error (MAE) is also a validation statistic that tells us how much of an error we can expect from CHIRPS satellite rainfall estimate. Similar to the root mean square error the value of mean absolute error ranges from 0 to  $\infty$  and a perfect value is zero.

$$MAE = \frac{1}{n} \sum_{i=1}^n (O_i - P_i) \quad (4)$$

where  $O_i$  is the meteorological gauge rainfall value and  $P_i$  is the CHIRPS rainfall value.

v Mean bias error

Mean bias error is primarily used to estimate the average bias in the CHIRPS rainfall value. The value of MBE ranges from  $-\infty$  to  $\infty$  and its positive and negative value indicates an overestimation and underestimation of CHIRPS data products, respectively (Fenta et al. 2018; Bayissa et al. 2017). It was calculated using the following equation.

$$MBE = \frac{1}{n} \sum_{i=1}^n (O_i - P_i) \quad (5)$$

where  $O_i$  is the observation value and  $P_i$  is CHIRPS rainfall value.

### Spatial-temporal variability and trend analysis of rainfall

The spatial variability of rainfall was calculated using the coefficient of variation (CV) and the standardized anomaly index (SAI). The data set was analyzed via spreadsheet tools in MS Excel and the graphs were mapped with ArcGIS software. Inverse distance weighting was applied for spatial interpolation. The Mann-Kendall's trend test (Mann 1945; Kendall 1975) and the Sens slope estimator (Theil 1950; Sen, 19680) were also used to identify and analyze possible trends in rainfall data.

**Coefficient of variation (CV)**

The annual, seasonal, and monthly time series variability of the rainfall in the study area was examined by calculating the coefficient of variation (CV) (Muthoni et al. 2019). According to the classification of Asfaw et al. (2018), a CV below 20 is less variable, a CV between 20 and 30 is moderately variable, and a CV above 30 indicates high variability. It was calculated using the formula:

$$CV(\%) = \left( \frac{\sigma}{\mu} \right) 100 \tag{6}$$

Here, CV is the coefficient of variation of the rainfall,  $\sigma$  is the standard deviation, and  $\mu$  is the mean rainfall for the selected time scales. A higher CV value indicates greater variability in rainfall and vice versa.

**Standardized anomaly index (SAI)**

The standardized anomaly index (SAI) was used as a descriptor of the rainfall variability, which indicates the number of standard deviations by which a rainfall event deviates from the average of the years under consideration (Funk et al. 2015). It has also been calculated to determine the dry and wet years on the records and is used to assess the frequency and severity of droughts (Alemu and Bawoke 2020). The SAI value is classified as extremely wet ( $SAI > 2$ ), very wet ( $1.5 \leq SAI \leq 1.99$ ), moderately wet ( $1 \leq SAI \leq 1.49$ ), almost normal ( $-0.99 \leq SAI \leq 0.99$ ), moderately dry ( $-1.49 \leq SAI \leq -1$ ), very dry ( $-1.99 \leq SAI \leq -1.5$ ), and extremely dry ( $SAI \leq -2$ ) (Funk et al. 2015) and is calculated as follows:

$$SAI_i = \frac{X_i - \bar{x}}{\sigma} \tag{7}$$

where SAI<sub>i</sub> is the standardized anomaly index in the year *i*, and  $X_i$  is the rainfall value for the respective year;  $\bar{x}$  is the long-term mean rainfall during the observation and  $\sigma$  is the standard deviation of the rainfall during the observation period. In comparison, negative values indicate a drought period, while the positive ones indicate above-average rainfall (wet situation) (Muthoni et al. 2019; Alemu and Bawoke 2020).

**MK trend test and Sen’s slope estimator**

The trend analysis was performed using the MK trend test and the Sen’s slope estimator (Mann 1945; Kendall 1975), using a modified package included in the statistical software R (RStudio) which was developed by the R Development Core Team (Core Team 2015). The MK test is the most

widely used nonparametric test used to detect monotonous trends in a series of environmental data, climatic data, or hydrological data (Gocic and Trajkovic 2013; Feng et al. 2016). The trends determined with the MK test are less influenced by outliers, missing values, and uneven data distribution since its statistics are based on the (+ or –) sign and not on the values of the random variables (Mann 1945; Kendall 1975; Belay et al. 2019). Therefore, the MK trend test is highly recommended by the World Meteorological Organization for general use in trend analysis. In this study, we have tested the null hypothesis (H0) with no trend, i.e., H. the observations  $x_i$  are randomly ordered in time, tested against the alternative hypothesis (H1), in which there is a monotonous (increasing or decreasing) trend in the time series based on the MK test (Mann 1945; Kendall 1975). Mann-Kendall’s test S was calculated using the following formula:

$$S = \sum_{i=1}^{n-1} \sum_{j=i+1}^n \text{Sign}(x_j - x_i) \tag{8}$$

where  $x_i$  and  $x_j$  are sequential data values for the time series data of length *n* and,

$$\text{Sign}(x_j - x_i) = \begin{cases} 1 & \text{if } (x_j - x_i) > 0 \\ 0 & \text{if } (x_j - x_i) = 0 \\ -1 & \text{if } (x_j - x_i) < 0 \end{cases} \tag{9}$$

It was found that if the number of observations exceeds 10, the statistic S is identical and independently distributed with the mean and E (S) becomes zero (Kendall 1975). In this case, the variance statistic is given as follows:

$$\text{Var} (S) = \frac{1}{18} \left[ n(n - 1)(2n + 5) - \sum_{i=0}^m t_i(t_i - 1)(2t_i + 5) \right] \tag{10}$$

where *n* is the number of observations, *j* is the number of bound groups in the time series, and  $t_p$  is the number of data points in the *p*th group. The test statistic Z is calculated as follows:

$$Z = \begin{cases} \frac{S-1}{\sqrt{\text{Var} (S)}} & \text{for } S > 0 \\ 0 & \text{for } S = 0 \\ \frac{S+1}{\sqrt{\text{Var} (S)}} & \text{for } S < 0 \end{cases} \tag{11}$$

The existence of a statistical significance trend is assessed with the significance level = 0.05 to test either a monotonous upward or downward trend. Positive and negative values of Z indicate an upward and downward trend, respectively. The null hypothesis is rejected if the absolute value of Z is greater than the critical values or the *p*-value is less than the selected significance level (= 0.05 or 0.1). If the null hypothesis is rejected, the result is said to be statistically

significant. On the other hand, the magnitude of the trends was calculated using the Theil-Sen's slope estimator (Theil 1950; Sen 1968). The method is a robust non-parametric estimator that does not react to missing values or outliers. It also provides consistent performance in statistical metrics of standard deviation, mean square error (RMSE), and slope estimator bias versus linear regression. The Theil-Sen test estimates the median of the slopes ( $\beta$ ) using the following equation (Theil 1950; Sen 1968):

$$\beta = \text{median} \left( \frac{x_j - x_i}{j - i} \right) \quad (12)$$

whereby  $\beta$  represents the median value of the slope values between the data measurements  $x_i$  and  $x_j$  in the time steps  $i$  and  $j$  ( $i < j$ ) accordingly. The positive value of  $\beta$  indicates an increasing trend, while the negative value of  $\beta$  indicates a decreasing trend in the time series. The sign of  $\beta$  reflects the direction of the data trend, while its value indicates the steepness of the trend (Alemu and Bawoke, 2020; Asfaw et al., 2018).

## Results and discussion

### Evaluation of CHIRPS rainfall data

This study examined the performance of CHIRPS rainfall data on monthly, seasonal, and annual timescales for use in spatiotemporal variability and trend assessment of rainfall. The evaluation was carried out based on meteorological measuring point data. Table 2 shows the results of the validation of CHIRPS rainfall data using data from meteorological measuring stations. The difference between the recorded mean monthly rainfall of the station and the corresponding values from the CHIRPS data is presented separately for each station in Fig. 2. In general, the result shows a very consistent agreement between the data from the weather station and the CHIRPS rainfall estimates on monthly timescales. The values of the correlation coefficient ( $r$ ) were high for the three stations with values around 0.99. The relatively lowest correlation coefficient (0.64) was obtained at the Nefas Mewcha weather station.

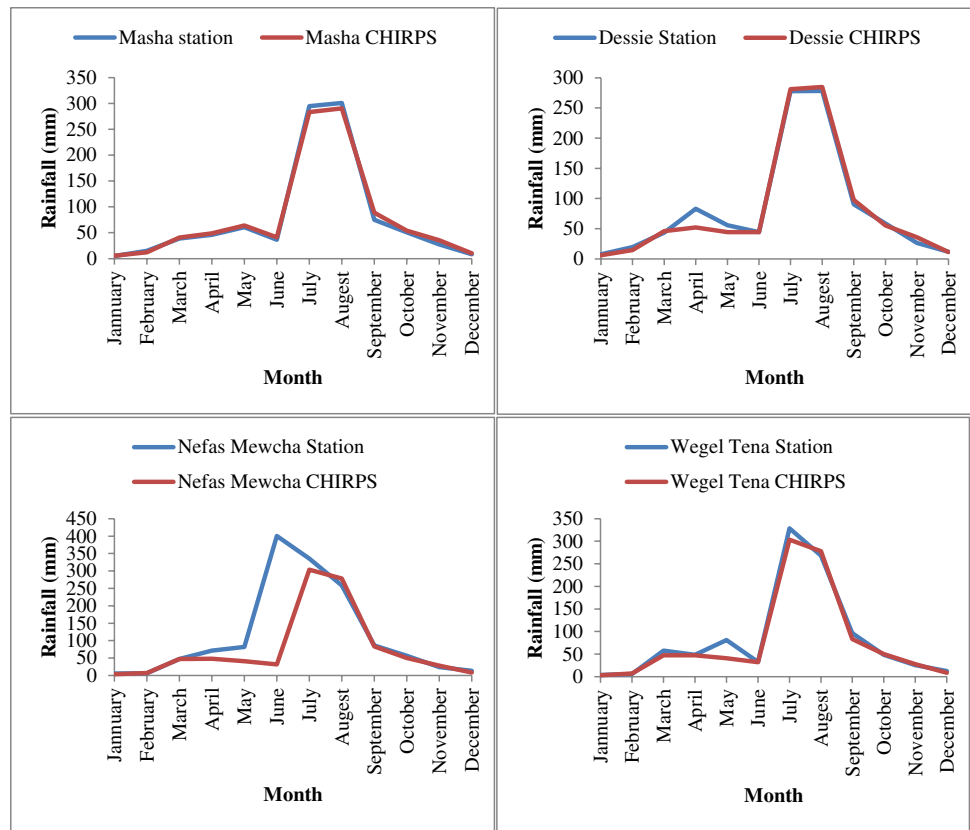
In addition, the monthly mean values of the Nash Sutcliffe efficiency coefficient (NSE) for all station locations were between 0.32 and 0.99 (Table 2). The monthly comparison of the rainfall data with statistical MAE, MBE, and RMSE values showed a good performance of the CHIRPS rainfall estimates over the Beshilo sub-basin (Table 2). As can be seen from the table, the monthly CHIRPS rainfall products were underestimated by approximately  $-2.029$  mm,  $-38.13$  mm,  $-6.67$  mm for Dessie, Nefas Mewcha, and Wegel Tena stations, respectively. On the other hand, the monthly CHIRPS rainfall data at the Masha stations was

**Table 2** Average statistical analysis of rainfall on monthly, seasonal, and annual timescales for the weather station and CHIRPS rainfall data

Monthly time scale	Dessie	Masha	Nefas Mewcha	Wegel Tena
R	0.99	0.99	0.644	0.99
NSE	0.987	0.995	0.319	0.978
MAE	6.746	5.432	42.284	9.145
MBE	-2.029	1.26	-38.139	-6.673
RMSE	10.478	6.84	107.85	14.874
<i>Bega</i> (October–February)				
R	0.878	0.824	0.259	0.279
NSE	-0.135	-0.135	-0.245	-0.267
MAE	22.944	12.323	55.58	41.924
MBE	-10.393	9.7	-33.338	-17.387
RMSE	25.836	15.444	84.966	47.187
<i>Belg</i> (March–May)				
R	0.74	0.995	0.747	0.541
NSE	0.431	0.987	0.37	-0.118
MAE	38.005	2.78	51.067	50.05
MBE	-12.79	2.78	-15.788	-17.67
RMSE	64.87	6.553	71.118	76.951
<i>Kiremt</i> (June–September)				
R	0.54	0.68	0.17	0.69
NSE	-0.557	0.352	-2.377	0.399
MAE	33.43	42.656	46.742	28.736
MBE	18.43	2.744	-27.027	-8.716
RMSE	55.338	49.717	57.035	33.508
Annual time scale				
R	0.65	0.9	0.5	0.4
NSE	0.14	0.65	0.15	0.26
MAE	9.8	13.8	23.013	31.14
MBE	24.04	30.832	-35.013	-28.11
RMSE	49.1	38.25	48.78	58.6

overestimated by about 1.26 mm. The minimum MAE (5.43 mm) and the maximum MAE (42.28 mm) were recorded in the Masha and Nefas Mewcha stations, respectively. The RMSE values ranged from 6.84 to 107.85. Based on the statistical measurements (Table 2), the monthly CHIRPS rainfall products at the stations Masha and Dessie do better than at the other two stations. In general, the overall performance assessment of the CHIRPS rainfall estimates demonstrated the potential of the CHIRPS rainfall products for various applications. This includes rainfall trends and variability studies in the study area. The present result is in line with previous studies carried out by Alemu and Bawoke (2020) in the Amhara regions of Ethiopia, Ayehu et al. (2018) in the UBNB of Ethiopia, Dinku et al. (2018) on east Africa, and Bayissa et al. (2017) and Bayable et al. (2021) in the West Harerge zone of Ethiopia.

**Fig. 2** Performance of CHIRPS rainfall data with rainfall data from meteorological stations based on the mean monthly rainfall in the Beshilo sub-basin



The performance of the CHIRPS rainfall products was also assessed and shown in Table 2 for each season of the Beshilo sub-basin. This is because a different amount of rainfall is recorded. The table shows a good agreement between the CHIRPS rainfall estimates and the rainfall from the weather station for the *Bega* season (October–January) with correlation coefficients ( $r$ ) ranging from 0.26 to 0.88 and NSE values between 0.15 and 0.35 found for all station locations. Likewise, the CHIRPS rainfall data in the *Belg* season was in very good agreement with the data from the observation stations, with the  $r$ -value between 0.54 and 0.99 and the NSE values for all station locations between 0.21 and 0.98 positions. In addition, good agreement between the CHIRPS products and the gauging stations with correlation coefficients ( $r$ ) ranging from 0.17 to 0.69 was observed in the *Kiremt* season. The maximum correlation coefficient ( $r = 0.69$ ) was obtained at the locations of the Wegel Tena station, while the correlation coefficient for the location of the Nefas Mewcha station ( $r = 0.26$ ) is weak.

In the *Bega* season, the CHIRPS rainfall data at the Dessie, Nefas Mewcha, and Wegel Tena stations in the study area were underestimated, while the rainfall data from the CHIRPS satellite at the locations of the Masha station in the study area was overestimated by about 9.7 mm. Similarly, in the *Belg* season, the CHIRPS rainfall data at the Dessie,

Nefas Mewcha, and Wegel Tena stations were underestimated. On the other hand, at the Masha station location, it was overestimated by about 2.78 mm. The rainfall data from CHIRPS were underestimated during the *Kiremt* season at the stations Nefas Mewcha and Wegel Tena and overestimated at the stations Dessie and Masha (Table 2). For the seasons *Belg* and *Bega*, the minimum MAE (2.78 mm) and maximum MAE (55.58 mm) were recorded in the stations Masha and Nefas Mewcha. This indicates that the CHIRPS rainfall data for all seasons correspond to the rainfall data in the study area. The result of this study agrees with previous studies by Bayissa et al. (2017) and found that CHIRPS are the most reliable satellite-based rainfall data on decadal, monthly, and seasonal timescales in the UBNB. In addition, Bayable et al. (2021) also reported the existence of a significant match between rainfall data from CHIRPS and monitoring stations west of the Harerge Zone in Ethiopia during the *Belg*, *Bega*, and *Kiremt* seasons.

On the annual timescale, an excellent agreement was also observed between the weather stations and the CHIRPS estimates, with the values of the correlation coefficient ( $r$ ) being between 0.4 and 0.9. The cumulative values of CHIRPS rainfall were underestimated at the Nefas Mewcha and Wegel Tena stations, while they were overestimated at the Dessie and Masha stations (Table 2). In addition, CHIRPS showed NSE values between 0.14 and 0.65 and

RMSE between 38.25 and 58.6 for all station locations. The result was consistent with the results of previous studies in most parts of Ethiopia (Ayehu et al. 2018; Dinku et al. 2018; Fenta et al. 2018; Alemu and Bawoke 2020; Bayable et al. 2021). Overall, the CHIRPS rainfall data showed a very high performance for assessing the spatial distribution and temporal trends of rainfall in the Beshilo sub-catchment area of the UBNB.

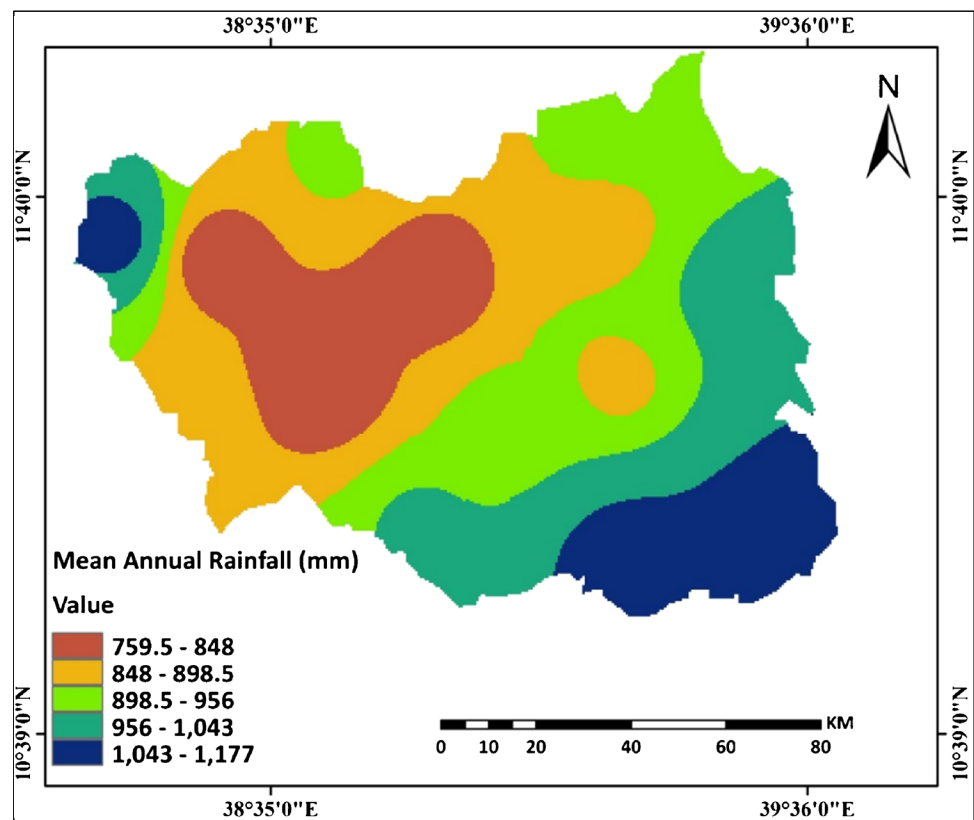
### Annual and seasonal rainfall distribution

The mean annual CHIRPS rainfall estimate (1983–2019) for the Beshilo sub-basin was 946.06 mm. The minimum and maximum rainfall recorded were 759.5 and 1177 mm, respectively (Fig. 3). Only five station locations recorded rainfall of more than 1000 mm, while the remaining ten station locations recorded rainfall amounts of less than 1000 mm. The highest levels of rainfall were observed in the western and southeastern parts of the study area. The lowest rainfall values, however, were observed in the central-western part of the study area. The highest annual rainfall values (1043–1177 mm) were measured around Dessie, Lay Gayint, Tulu Awlia, and the Dessie Zuria stations (Fig. 3). Torke and the southeastern part of Tach Gayint and the northern part of Simada district recorded the least annual rainfall (759.5–848 mm). The heaviest annual rainfall was observed at upper elevations than at lower elevations.

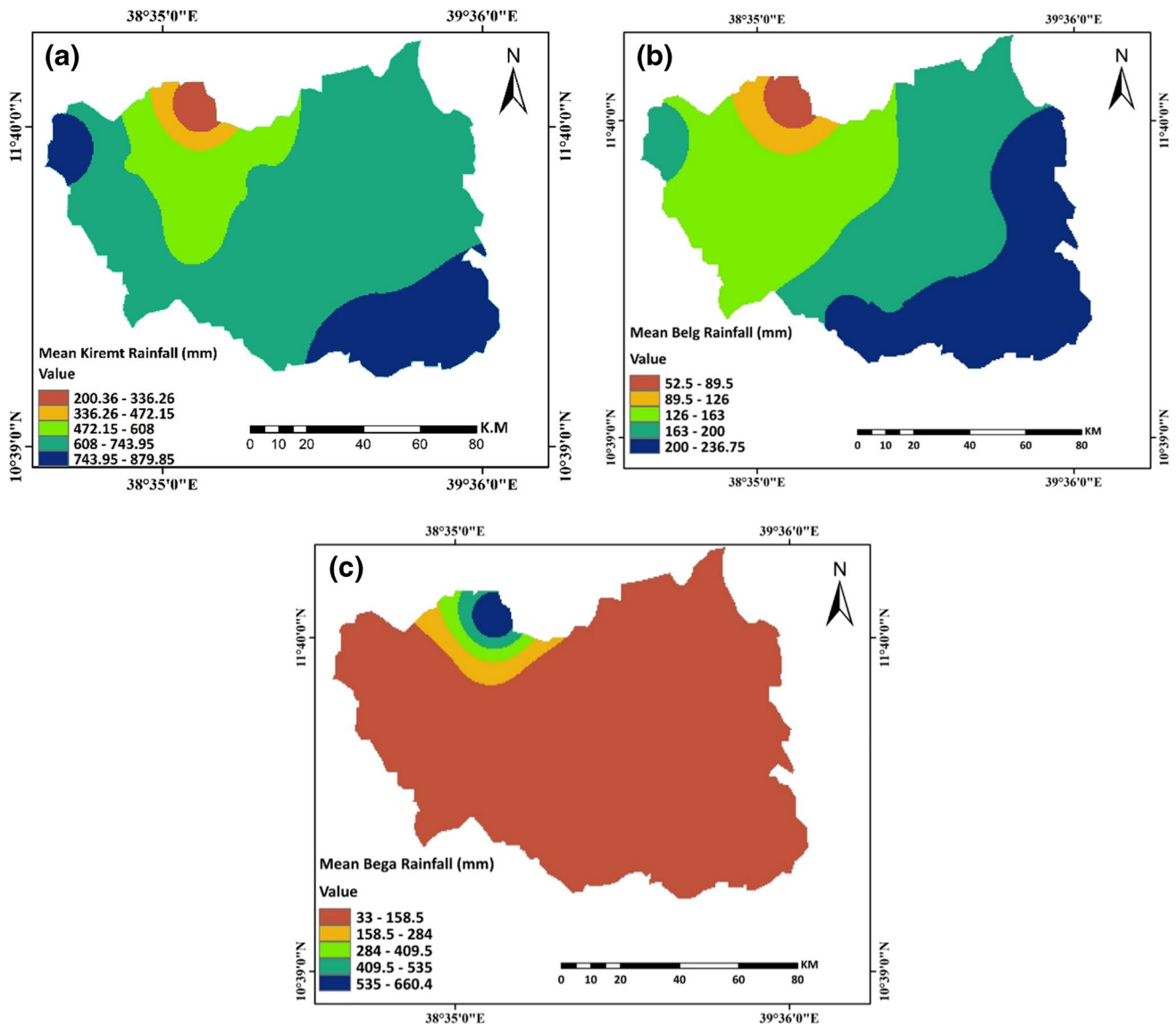
Previous studies on rainfall distribution also reported a strong correlation between rainfall and altitude in their respective study areas (Addisu et al. 2015; Gummadi et al. 2018; Ademe et al. 2020; Alemu and Bawoke 2020; Bayable et al. 2021).

Rainfall in the Beshilo sub-basin is bimodal. The spatial rainfall patterns for all seasons (1983–2019) are shown below (Fig. 4a, b, and c). Much of the rainfall is concentrated in *Kiremt* (main rainy season), which accounts for more than 71% of the annual rainfall with a peak in July and August (Fig. 4a and Fig. 5). The highest rainfall values were recorded in the western and south-eastern parts of the study area, while the lowest rainfall values were recorded in the north-western parts of the study area. Another notable contribution to the total annual rainfall occurred in the *Belg* (small rainy season) with 18.83%. During the *Belg* season, the southern and northeastern parts of the study area show the highest rainfall values, while the lowest rainfall values were recorded in the north-western parts of the study area. The rainfall of the *Kiremt* and *Belg* seasons followed almost the same spatial distribution as the annual rainfall. In addition, there was a strong correlation between rainfall and altitude this season. Similarly, the *Bega* season accounts for 9.84% of the total annual rainfall in the study area. From Fig. 4c, it can be seen that the highest rainfall values were recorded at the top of the northwestern part of the investigation area. The result was in agreement with the results of

**Fig. 3** Spatial distributions of long-term mean annual rainfall (mm) in the study area (1981–2019)

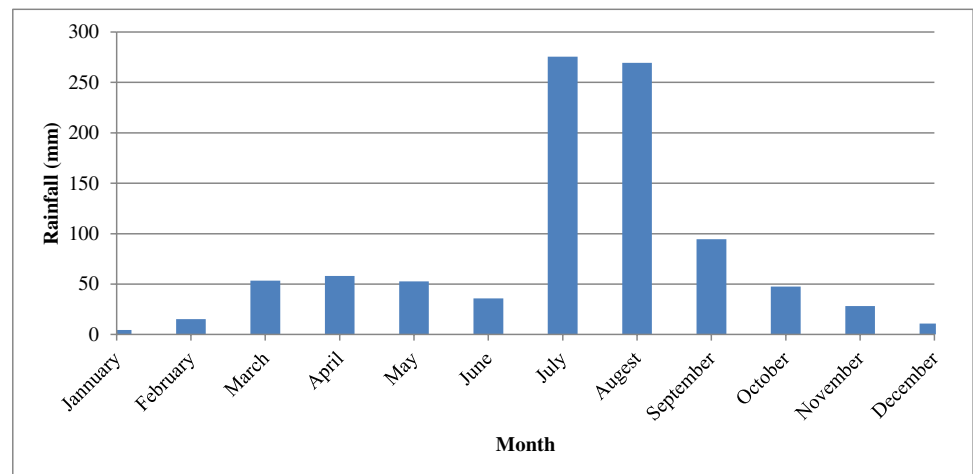






**Fig. 4** Spatial distribution of the long-term mean *Kiremt* rainfall (mm) (a), the mean *Belg* rainfall (mm) (b), and the mean *Bega* rainfall (mm) (c) of the Beshilo sub-basin (1981–2019)

**Fig. 5** Long-term average monthly rainfall of the Beshilo sub-basin (1981–2019)



previous studies (Kiros et al. 2017; Gummadi et al. 2018; Alemu and Bawoke 2020; Geremew et al. 2020; Bayable et al. 2021) in most parts of Ethiopia.

The monthly rainfall was determined by averaging the rainfall of each month during the study period (1981–2019). The long-term mean monthly rainfall is shown in Figs. 5 and 6. These figures show that April, July, August, and September were the wettest months, while January, February, November, and December were the driest months. In March, May, June, and October, there was relatively scant rainfall. The highest rainfall was recorded in July and August, while the lowest rainfall was recorded in January (Fig. 5). Alemu and Bawoke (2020) also found that June, July, August, and September were the main rainy months, and November, December, January, February, and March were the driest months in the Amhara region of Ethiopia.

**Annual and seasonal spatio-temporal variability of rainfall**

Figure 7 shows the spatial distribution of the annual variability in rainfall using coefficients of variation in the study area. This figure shows that there was moderate variability

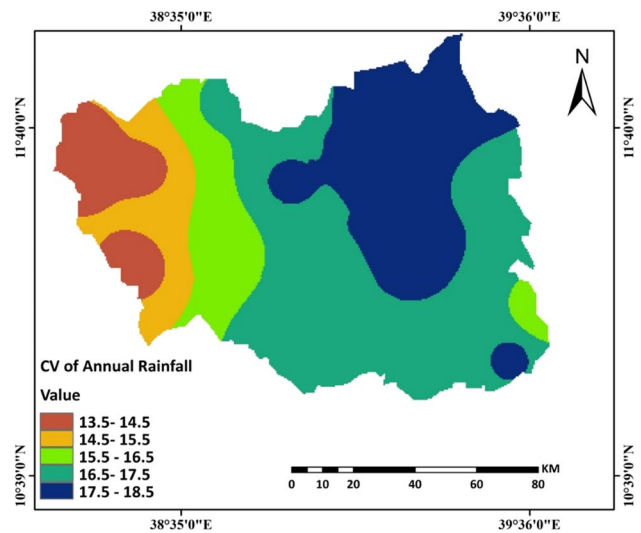


Fig. 7 Spatial distribution of long-term CV (%) of annual rainfall in Beshilo sub-basin (1981–2019)

in annual rainfall between years based on the coefficient of variation. The variability between the years was relatively greater in the northern and central-eastern parts of the study

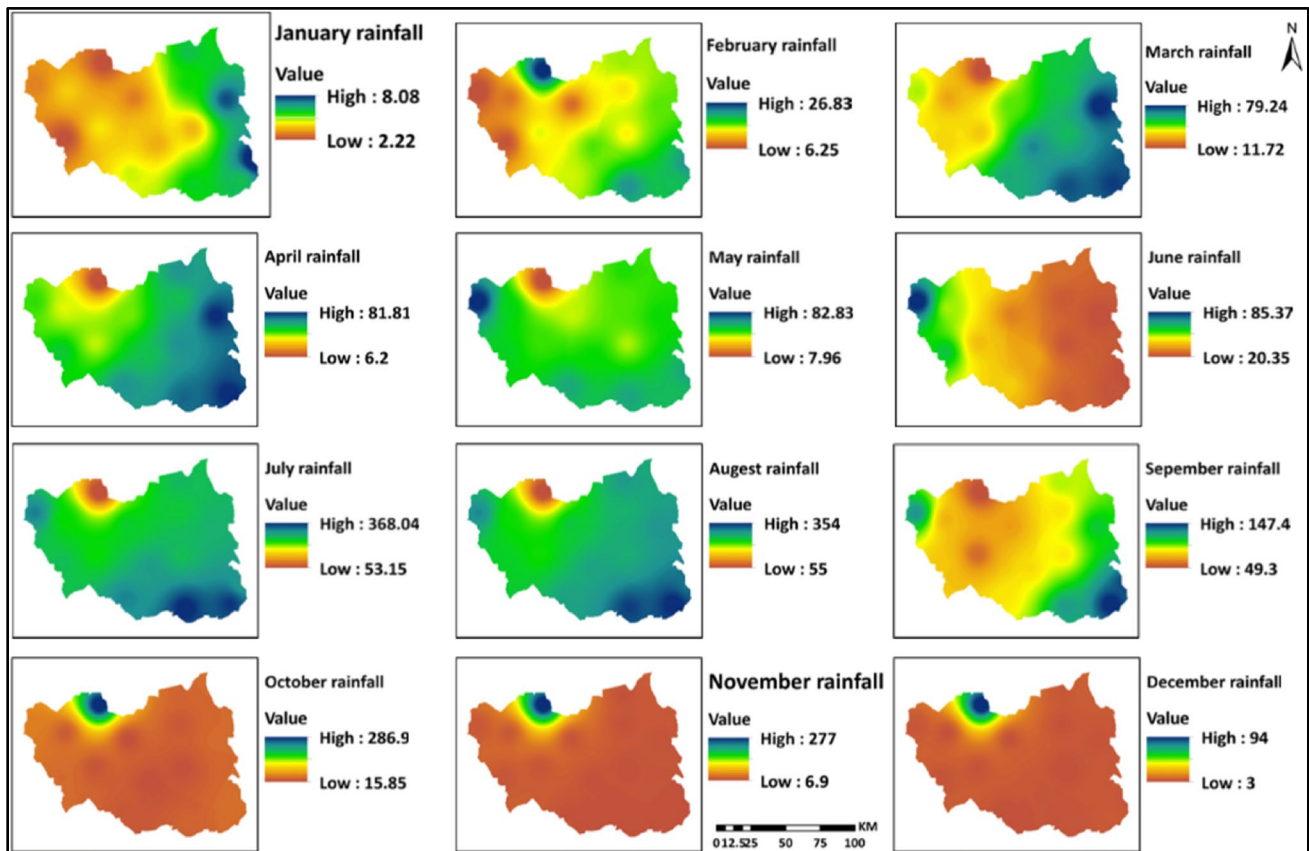
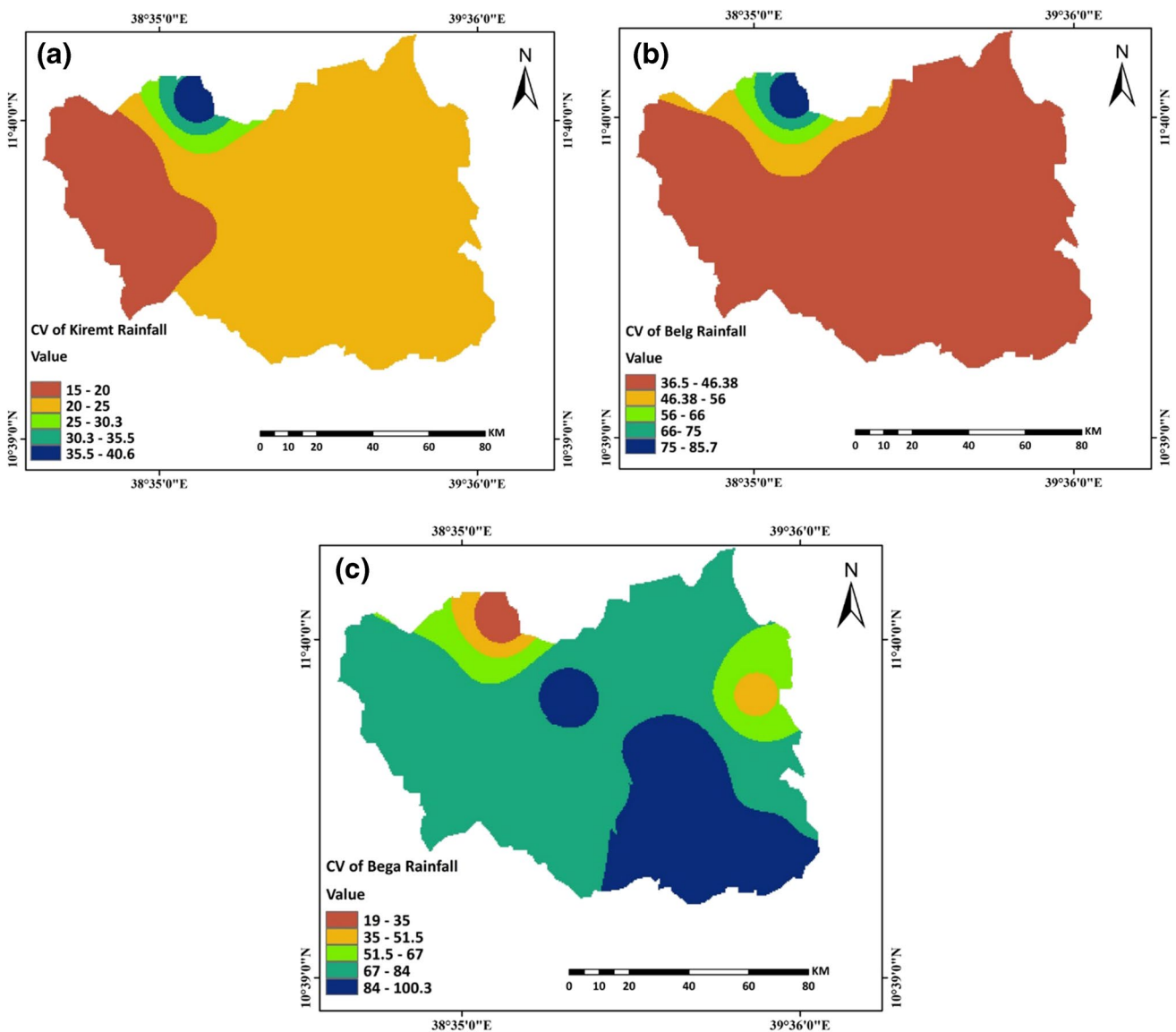


Fig. 6 Spatial distributions of the long-term average monthly rainfall of Beshilo sub-basin (1981–2019)

area ( $CV > 17\%$ ). In contrast, the variability in annual rainfall is lower in the western parts of the area (14.5%). High variability of rainfall was found in the northern and central-eastern parts of the station locations including Wegel Tena, Wadla, Tenta, and Dawnt (Fig. 7). Areas with high annual rainfall showed less variation between years, while areas with low annual rainfall showed relatively greater variation between years. The results of this study were in agreement with previous studies by Alemayehu et al. (2020) and Marie et al. (2021), who showed moderate variation in rainfall in the Alwero watershed in western Ethiopia and north-western Ethiopia. It also agrees with the results of Yimer (2018), who reported moderate rainfall variability between years in the northeastern highlands of Ethiopia. In addition, the

inverse relationship between rainfall variability and mean annual rainfall confirms the results of (Gummadi et al. 2018; Dawit et al. 2019; Alemu and Bawoke 2020; Geremew et al. 2020; Bayable et al. 2021).

The spatial distributions of the CV of seasonal rainfall in the study area are shown below (Fig. 8a, b, and c). As shown in the figure, the seasonal rainfall variability was higher than the annual rainfall variability. The rainfall variability of *Kiremt* is less than 20% in the western parts, while the highest CV values (35.5–40.6%) were observed in the *Belg* and *Bega* seasons. *Kiremt*'s rainfall variability appeared to be relatively stable. The coefficients of variation (CVs) for the area during the *Belg* season (36.5–85.7%) turned out to be significant (Fig. 8b). Similarly, the highest values of the CV captured the



**Fig. 8** Spatial distribution of the long-term CV (%) of the rainfall of the season *Kiremt* (a), *Belg* (b), and *Bega* (c) in the lower basin of Beshilo (1981–2019)

selection of the northwestern parts of the study area. With a CV of up to 100.3%, the *Bega* rainfall amount was extremely variable compared to the other seasons. The maximum CV during *Bega* rainfall was observed in the central northern and southeastern parts of the study area. Such annual and seasonal variability in rainfall could affect farmers' ability to mitigate the effects of climate change and variability (Lalego et al. 2019). The result of our determination is supported by the findings of Alemu and Bawoke (2020), Geremew et al. (2020), and Marie et al. (2021), who reported more moderate variability in annual rainfall than seasonal rainfall, as many studies (e.g., Asfaw et al. 2018; Yimer 2018; Belihu et al. 2018; Mohammed et al. 2018; Alemu and Bawoke 2020; Geremew et al. 2020; Bayable et al. 2021) in different parts of Ethiopia reported that rainfall from *Bega* and *Belg* was more variable than rainfall from *Kiremt*. In addition, this result agrees with the results of Marie et al. (2021) in northwestern Ethiopia and Abegaz (2020) across central Ethiopia, who noted that the *Belg* season rainfall was more variable than the *Kiremt* season rainfall.

The spatial distribution of the monthly rainfall CV (%) of the study area is shown in Fig. 9. It was found that not only the seasonal rainfall distribution but also the monthly rainfall distribution in the Beshilo sub-basin is variable. The

coefficient of variation (CV) is between 16.55 and 222.7%. It was found to be highest in November, December, January, May, and February (CV > 175%). In contrast, in some parts of the study area, the months of August, July, and November showed the lowest inter-month variability (CV < 25%). The remaining months had coefficients of variation (CVs) between 27.35 and 165.73%, indicating increased rainfall variability during these months. The result of this study agrees with the study by Marie et al. (2021), who reported the highest CV during the February and January months and the lowest CV during the August and July months across central Ethiopia. In addition, a study carried out in the West Harerge Zone of Ethiopia by Bayable et al. (2021) reported the highest CV in January, February, and November, and the lowest CV in July and August.

### Annual and seasonal standardized anomalies of rainfall

The standardized annual and seasonal rainfall anomalies (1981–2019) over the entire study area are presented in Fig. 10. The result of the standardized anomaly index (SAI) showed the existence of interannual variability with 53.84% dryness tendency and 46.15% wetness tendency over the study area on

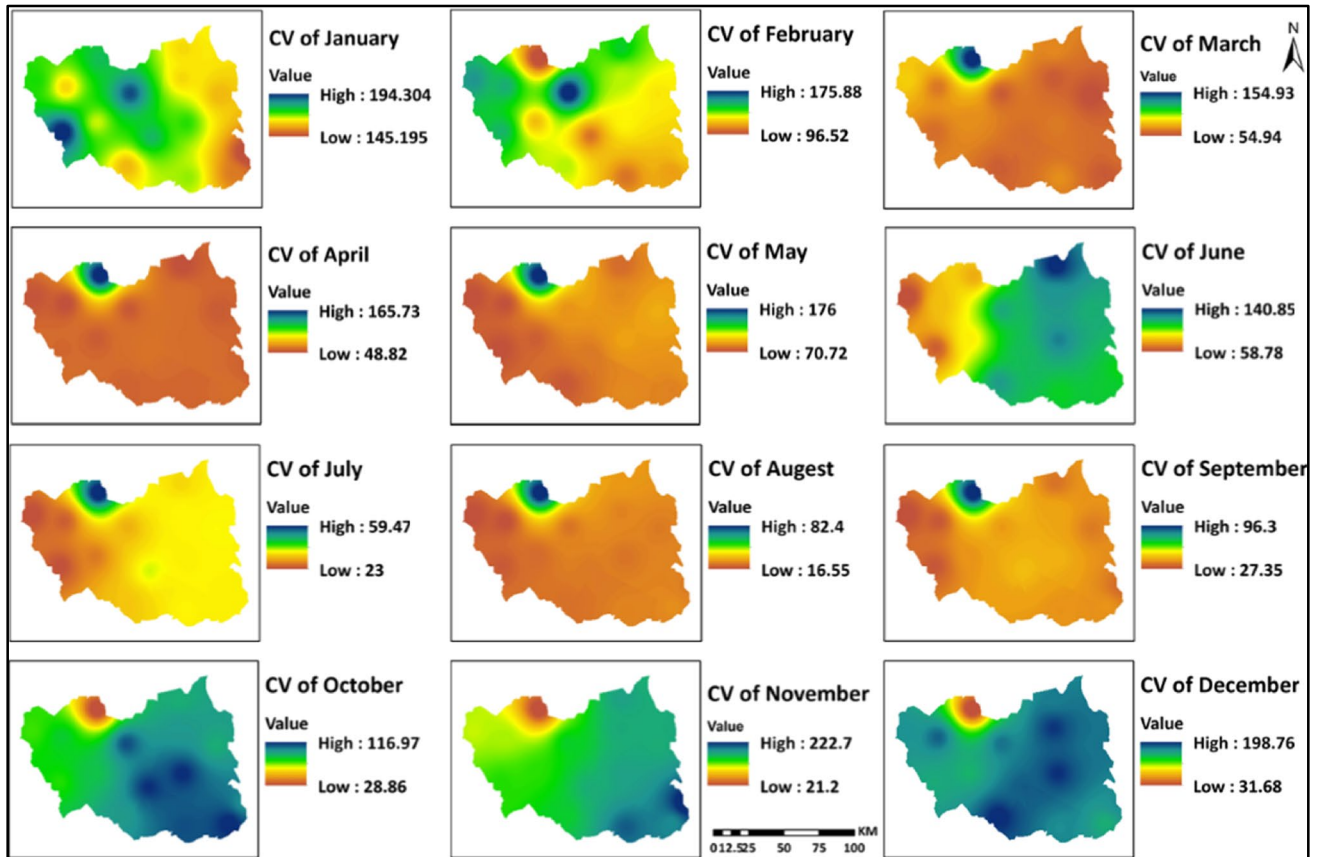
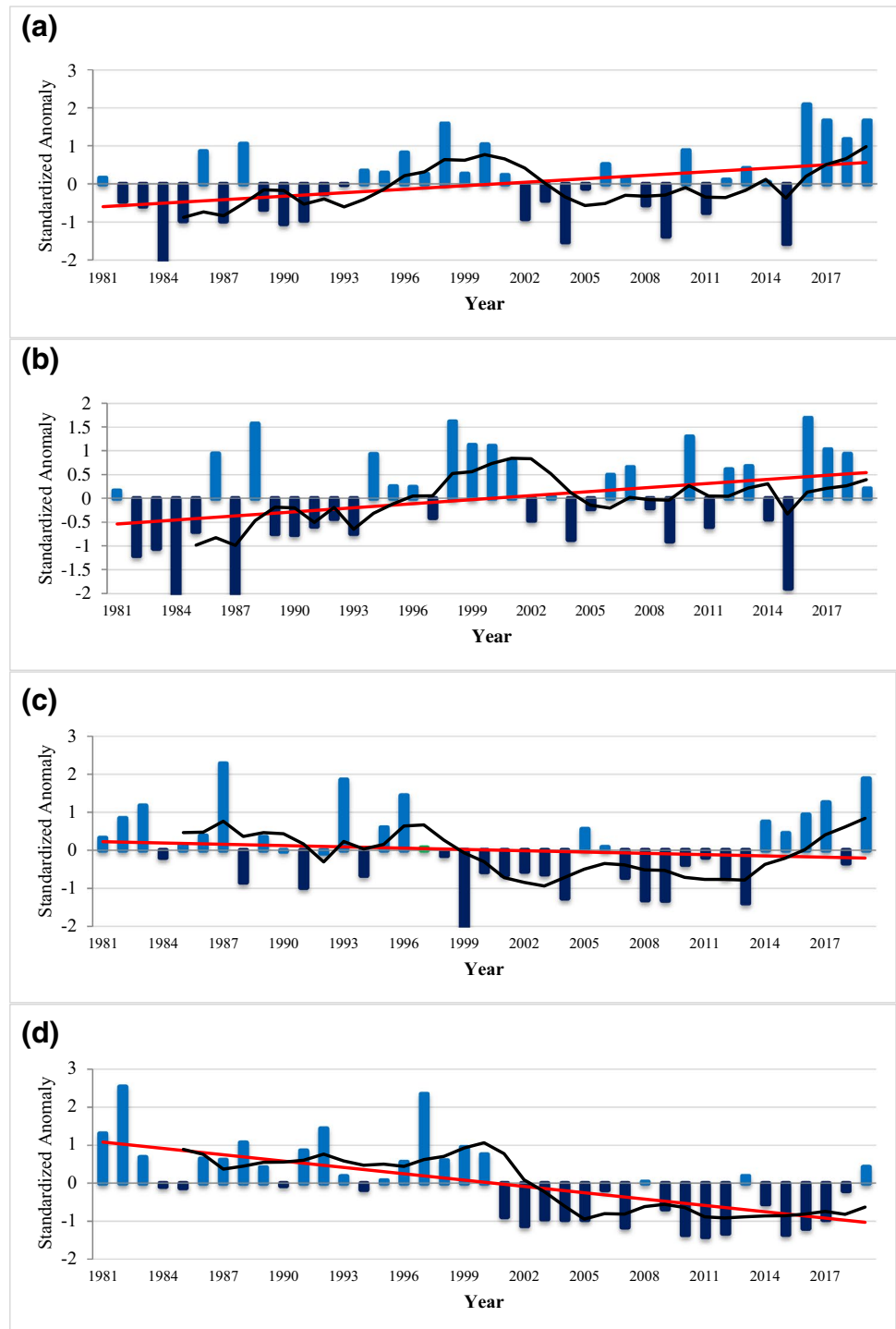


Fig. 9 Spatial distribution of long-term monthly rainfall CV (%) of Beshilo sub-basin (1981–2019)

an annual basis (Fig. 10a). The highest (extremely wet) positive anomaly (SAI = about 2.2) was observed in 2016, while the highest (extremely dry) negative anomaly (SAI = 2) was observed in 1984. The long-term annual rainfall anomalies were negative in 1981, 1986, 1988, 1993–2001, 2006/2007, 2010, 2012–2014, and 2016–2019 (Fig.10a). The results of this study agree with the results of Alemayehu et al. (2020) in the Alwero watershed in western Ethiopia, Bayable et al. (2021) in the

western Harerge zone of Ethiopia, Geremew et al. (2020) in the Enebsie Sar Midir district in northwest Ethiopia, and Alemu and Bawoke (2020) in the regional state of Amhara in Ethiopia. According to Funk et al. (2015), fourteen nearly normal years (two moderately dry years (1982 and 1983), one severe (2015), and two extremely dry years (1984 and 1987)) were identified. In contrast, the study area experienced extremely wet years in 2016, while 1998, 2017, and 2019 showed very wet years.

**Fig. 10** Standardized anomalies of time series of the average annual (a), Kiremt (b), Belg (c), and Bega (d) rainfall. The straight red line is the linear trend for the variables while the black curved line is the 5-year moving average



The result of this study also agrees with the findings of Abegaz (2020) and reports that years like 1987 were years of extreme drought over the central parts of Ethiopia. In addition, Alemayehu et al. (2020) identified positive standardized rainfall anomalies for years such as 1996, 1997, 1998, 1999, 2010, 2012, 2013, 2015, and 2016 in the Alwero watershed in western Ethiopia.

The results of the SAI's analysis of seasonal rainfall in the study area during the study period are also shown in Fig. 10b, c, and d. The percentage of negative anomalies was larger than positive anomalies in all seasons except *Kiremt*. Similarly, a study by Alemayehu et al. (2020) showed that the percentage of negative anomalies exceeded that of positive anomalies in all seasons except *Kiremt* in the Amhara region. Similar to the annual rainfall, interannual variability of the rainfall was found in the seasons *Kiremt*, *Belg*, and the *Bega*. These seasons had negative anomalies accounting for 48.7%, 53.84%, and 51.28%, respectively, during the years examined. Extremely dry conditions for *Kiremt* rains were experienced in 1984 and 1987. On the other hand, the highest negative anomaly was found in 1999 and 2011 in the *Belg* and *Bega* seasons, respectively. In the period from 2000 to 2018, the standardized rainfall anomalies were positive, except for the years 2008 and 2013 for the *Bega* season.

### Annual and seasonal rainfall trends

The results of the MK trend test and Sen's slope estimator analysis of monthly rainfall in the study area are presented in Table 3. The results of the analysis showed that there was a downward trend in February, March, April, and December (1981–2019). In contrast, a rising trend was observed in January, May, June, July, August, September, October, and November. The results of these decreasing and increasing trends for the monthly rainfall data were not significant in all months except June and November at a significance level of  $\alpha = 0.05$  (Table 3). The result of this

finding agrees with a study by Alemu and Bawoke (2020), which reports insignificant trends in all months except November in the Amhara region, to which our study area belongs. Another study conducted by Marie et al. (2021) also found no noticeable trend in monthly rainfall except for the February and September months in northwest Ethiopia. In addition, significant increasing trends were found by Tesfamariam et al. (2019) for the November month at Billate and Konso stations and the June month at Ziway station in the Rift Valley Lakes basin of Ethiopia.

The seasonal rainfall showed a downward trend in the *Belg* and *Bega* seasons, while an upward trend was recorded in the *Kiremt* season (Table 4 and Fig. 10b, c, and d). Significant rising and falling trends at 0.05 were also observed in the seasonal rainfall amounts of *Kiremt* and *Bega*. In addition, the annual rainfall showed an upward trend (Table 4 and Fig. 10a) and this positive trend was not significant with a significant level of 0.05. This result agreed with the results of Viste et al. (2013) in southern Ethiopia and reported a decreasing trend in rainfall during the *Belg* season over different periods. In addition to this, Gebrechorkos et al. (2019) found a non-significantly decreasing (increasing) trend in eastern (western) parts of Ethiopia during the *Kiremt* season from 1981 to 2016. Mohammed et al. (2018) also reported that rainfall in the *Kiremt* season around Dessie, Haik, and Mekaneselem increased significantly from six meteorological stations and in *Belg* recorded a decrease at all stations examined in the South Wollo zone (1984–2014). Similarly, Weldegerima et al. (2018) found an insignificant upward trend on both seasonal and annual time scales in the Lake Tana Basin. In addition, Alemu and Bawoke (2020) found an insignificant increasing trend in annual and *Kiremt* rainfall (1981–2017) in the Amhara region of Ethiopia. Alemayehu and Bewket (2017b) also reported that the annual rainfall in most areas of the UBNB, to which the study area also belongs, shows statistically non-significant increases (Fig. 11).

**Table 3** MK trend analysis of basin wide monthly rainfall in the Beshilo sub-basin (1983–2019) at a significance level of  $\alpha = 0.05$

Month	Kendall's tau	S	<i>p</i> -value	Trend	Z-value	Sen's slope (mm/year)
January	0.14	105	0.2	Upward	1.28	0.055
February	−0.13	−94	0.26	Downward	−1.13	−0.19
March	−0.06	−43	0.61	Downward	−0.51	−0.32
April	−0.18	−67	0.42	Downward	−0.8	−0.09
May	0.06	48	0.57	Upward	0.57	0.33
June	0.23	173	0.037	Upward	2.08*	0.64
July	0.15	111	0.18	Upward	1.33	1.77
August	0.14	101	0.23	Upward	1.21	1.06
September	0.27	23	0.53	Upward	0.15	0.15
October	0.185	137	0.1	Upward	1.65	0.63
November	0.34	249	0.003	Upward	3*	0.45
December	−0.01	−9	0.92	Downward	−0.1	−0.009

\*Significant at  $\alpha = 0.05$

**Table 4** MK trend analysis of basin wide annual and seasonal rainfall (1983–2019) in the Beshiho sub-basin at a significance level of = 0.05

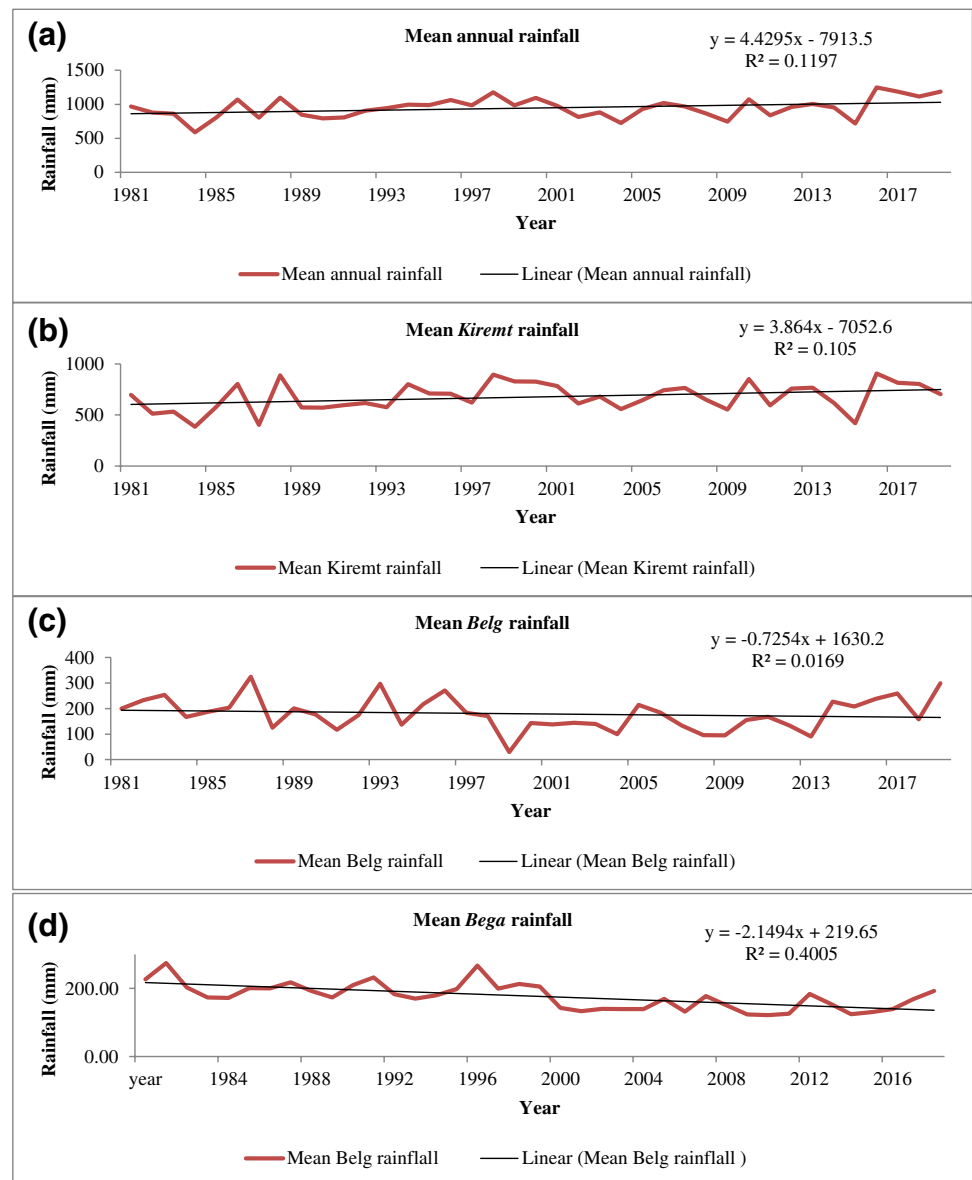
	Kendall's tau	S	p-value	Trend	Z-value	Sen's slope (mm/year)
Annual rainfall	0.21	153	0.07	Upward	1.84	4.65
<i>Kiremt</i> rainfall	0.035	175	0.035	Upward	2.1*	4.29
<i>Belg</i> rainfall	-0.11	-83	0.32	Downward	-0.99	-1.03
<i>Bega</i> rainfall	-0.46	-339	0.0	Downward	-4.09*	-2.04

\*Significant at  $\alpha=0.05$

In contrast, Wagesho et al. (2013) and Mulugeta et al. (2019) find a significantly reduced trend in *Kiremt* rainfall (at 0.1) over most parts of the Awash river basin. Likewise, Ademe et al. (2020) reported that there has been a significant decrease in rainfall for about 25% of locations around the entire agricultural region of Ethiopian highlands. Tabari et al. (2015) also reported

that annual rainfall decreased at most stations across Ethiopia. Moreover Cheung et al. (2008) showed a significant decreasing rainfall trend in the southwestern and central parts of Ethiopia during the *Kiremt* season. The difference in our result of the rainfall trend analysis to the studies mentioned above could be related to the difference in the study area and study period.

**Fig. 11** Long-term mean annual and mean seasonal rainfall (annual (a), *Kiremt* (b), *Belg* (c), and *Bega* (d)) of the Beshilo sub-basin (1981–2019)



## Conclusion

Several studies have shown that Ethiopia is vulnerable to climate change, and it will likely cause more frequent and more severe disasters. The adverse impacts of climate change could worsen existing economic and social challenges in the entire country, especially in areas where rain-fed agriculture and resources sensitive to climate change are prevalent. Climate change and weather extremes can be reduced if the information is available about the nature, extent, and location of their impacts. This is if appropriate adaptation options are to be designed.

This study examined seasonal and annual variations in rainfall in the Beshilo sub-basin of the UBNB using CHIRPS rainfall products. The spatiotemporal variability of rainfall showed that annual rainfall varied moderately from year to year. Meanwhile, high spatiotemporal variability of rainfall between the years was observed on seasonal and monthly time scales within the study area. The result coefficient of variation indicated that the seasonal rainfall in the dry season (*Bega*) showed a greater variability between years than in other seasons, which means a greater variability of rainfall in *Bega* than in other seasons. Similarly, rainfall was more variable during the short rainy season (*Belg*) than in the main rainy season (*Kiremt*). Based on the results of the annual standardized anomaly index, the percentage of negative anomalies in the study period (53.84%) exceeded the percentage of positive anomalies (46.15%). Furthermore, the percentage of negative anomaly was higher for all seasons of rainfall, except for *Kiremt*.

However, there was a decreasing trend in *Belg* and *Bega* rainfall during the periods studied. There was also a significant increase in monthly rainfall in June and November, and an insignificant decrease in February, March, April, and December. The rising trend for *Kiremt* rainfall was found to be significant ( $\alpha = 0.05$ ). Conversely, a significant downward trend was observed for the *Bega* season. From the result, it can be concluded that the rainfall in the study area is characterized by a high spatial and temporal variability. So it is imperative to adjust agricultural activities in response to rainfall variability and prepare adaptation strategies for climate change to increase the adaptability and resilience of rain-dependent smallholders. In this study, however, the lack of time and funds made it difficult to determine the inferential causes and effects of spatiotemporal variability of rainfall. As a consequence, more research is needed to determine the driving forces and implications of the spatiotemporal variability of rainfall.

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**Author contribution** Jemal Ali Mohammed: provide the main idea of the research, process and analyze the raw data, prepare the first version of the manuscript, and perform writing—review and editing; Zinet Alye Yimam: perform writing—review and editing.

## Declarations

**Competing interests** The authors declare no competing interests.

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