Analysis of spatial variability and temporal trends of rainfall in Amhara region, Ethiopia
Melkamu Meseret Alemu and Getnet Taye Bawoke

ABSTRACT
Understanding rainfall distribution in space and time is crucial for sustainable water resource management and agricultural productivity. This study investigated the spatial distribution and temporal trends of rainfall in Amhara region using time series rainfall data of Climate Hazards Group Infrared Precipitation with Stations (CHIRPS) for the period 1981–2017. Coefficient of variation, standardized anomaly index (SAI), precipitation concentration index (PCI) and seasonality index (SI) were used to evaluate rainfall variability and seasonality. Mann–Kendall’s test was also employed for rainfall trend analysis. Results showed that the region has been experiencing variable rainfall events that cause droughts and floods over different years. SAI also witnessed the presence of inter-annual variability of rainfall with negative and positive anomalies in 59.46% and 40.54% of the analyzed years, respectively. PCI and SI results implied that the area had irregular and strong irregular rainfall distribution. Trend analysis results showed an overall increase in the annual and seasonal rainfall (except winter) during the study period. The information obtained from this study could serve as a proxy for rainfall variability and trend in the study area which might be used as input for decision-makers to take appropriate adaptive measures in various agricultural and water resources sectors.

Key words | CHIRPS, Mann–Kendall test, precipitation concentration index, seasonality index, spatial distribution, temporal trends

INTRODUCTION
Climate change and variability are perceived as being the greatest threats to agricultural production and food security in sub-Saharan African countries, particularly for regions that depend on rain-fed agriculture (Kisaka et al. 2015). Ethiopia, like other countries in the region, is highly exposed to climate change and variability and has experienced several food crises during the last decade (Viste et al. 2013). Rainfall is one of the most important climatic variables that has a direct and indirect impact on agricultural production and ecosystem health (Weldegerima et al. 2018). Erratic rainfall patterns and frequent extreme events such as droughts, floods and irregularities in seasonal rainfall amount and distribution are among the major climate-related catastrophes that have drastic ramifications on food security and economic growth (Cattani et al. 2018).

Analysis of the spatial distribution and the temporal trends of rainfall is crucial for water resource management, agricultural productivity and climate change mitigation (Ayalew et al. 2012). Moreover, analyzing both inter-annual and intra-annual trends in rainfall offers intuitive information on the dynamics of soil moisture in rain-fed systems (Zhao et al. 2015). Such spatial and temporal trend analyses of rainfall require long-term rainfall time series data at high temporal and spatial resolutions. Traditionally, meteorological stations have been used as the main source
of rainfall data. However, the use of meteorological stations for rainfall monitoring is less applicable in most parts of the world, especially in less developed countries in which the stations are typically sparse, poorly spatially distributed, and have data discontinuities (Kimani et al. 2017). This is also true in Ethiopia, particularly in Amhara regional state, where this study was conducted.

Different trend analysis studies have been conducted in Ethiopia at different spatio-temporal scales and came up with some contrasting results. For example, Seleshi & Zanke (2004) identified no trend in the annual and seasonal rainfall for northern and northwestern Ethiopia in the second half of the 20th century. Jury & Funk (2013) observed a declining trend in rainfall over southwestern Ethiopia in the period 1948–2006. On the other hand, a study by Mengistu et al. (2014) in the upper Blue Nile River basin (Ethiopia) exhibited statistically non-significant increasing trends in annual rainfall for the period 1981–2010. Gedefaw et al. (2018) used five representative meteorological stations in Amhara region to study variability of rainfall on monthly, seasonal, and annual time scales and reported a mix of significant positive and negative trends in the stations.

The majority of previous studies have been confined to data from a few meteorological stations, and are therefore spatially incomplete. In recent decades, satellite-derived rainfall products have been used for providing rainfall estimates on global scale at ever increasing spatial and temporal resolutions as a viable alternative to station observations (Cattani et al. 2018; Dinku et al. 2018). Moreover, satellite-derived rainfall estimates provide timely, repetitive, and cost-effective information about rainfall at different time scales from daily to annually, which makes them very crucial, particularly in drought monitoring and early warning systems (Toté et al. 2015; Muthoni et al. 2018). However, there are uncertainties associated with techniques for satellite rainfall estimates. The uncertainties may arise from spatio-temporal sampling errors, error from algorithms, and satellite instruments themselves (Gebremichael et al. 2005). These may affect the accuracy of satellite-derived rainfall estimates and may result in a significant error when they are used for different applications such as rainfall pattern and variability study. Thus, the reliability of the satellite-derived rainfall products need to be evaluated before using them for the intended applications.

Nowadays, there is a wide variety of satellite-based rainfall products derived from multiple data sources. Climate Hazards Group InfraRed Precipitations with Stations (CHIRPS) is a relatively new rainfall product with high temporal and spatial resolution, and is based on multiple data sources. CHIRPS provides long-term datasets (from 1981 onwards), which can be profitably exploited for the evaluation of rainfall trends. Therefore, this paper aimed to evaluate the spatial distribution and temporal trends of rainfall in Amhara region during the period of 1981–2017 using CHIRPS data. Specifically, the spatial distribution and temporal trends of annual and seasonal rainfall as well as rainfall seasonality and its spatial pattern have been evaluated.

**STUDY AREA AND DATA SOURCES**

**Study area**

The Amhara region (Figure 1) is located in the northwestern and northcentral parts of Ethiopia. Geographically, it lies between 9° 20’ and 14° 20’ N latitude and 36° 20’ and 40° 20’ E longitude. Its area is estimated at about 170,000 square kilometers and is divided into 11 administrative zones. Elevation ranges from 700 m to 4,620 m a.s.l. The area with the lowest elevation is located in the western Amhara, whereas high elevations are in the eastern and northeastern regions. Most of the region is on the highland plateau above 1,500 m and is characterized by rugged mountains, hills, valleys, and gorges. The livelihoods of the majority of the populations in the region are highly dependent on rain-fed agriculture. The region is characterized by erratic rainfall, high land degradation, and high rate of poverty (Ayalew et al. 2012). Erratic rainfall patterns and frequent extreme events cause crop failure and threaten the food security and livelihoods of the people in the region. Therefore, knowledge of the spatial and temporal variability of rainfall patterns in the region helps the local community to better plan sustainable adaptation and mitigation strategies and secure sustainable agricultural production.
Data sources

Meteorological stations’ data

Monthly rainfall data were collected from eight meteorological stations (Table 1) in the period between 2000 and 2010 from the National Meteorological Services Agency of Ethiopia to validate the satellite-derived rainfall products.

CHIRPS satellite data

In this study, monthly CHIRPS data from 1981 to 2017 were used. CHIRPS is quasi-global dataset (covering the area between 50° N and 50° S) developed by the U.S. Geological Survey Earth Resources Observation and Science Center in collaboration with the Climate Hazards Group at the University of California, Santa Barbara. It has spatial resolution of 0.05° and is produced using multiple data sources. CHIRPS is available online at http://chg.geog.ucsb.edu/data/chirps/. Details of CHIRPS can be found in Funk et al. (2015).

### METHODS

**Validation statistics**

In this study, the evaluation of the satellite rainfall products has been carried out for the period from 2000 to 2010 using measured rainfall data from eight independent weather stations in Amhara region at monthly and yearly temporal scales. For each validation weather station, the grid values of satellite rainfall estimates containing the stations were extracted and pair-wise comparisons with rain gauge values were undertaken using the commonly used statistical measures, such as Pearson correlation coefficient (R), mean error (ME), mean absolute error (MAE), and percent bias (PB) (Dinku et al. 2018). The correlation coefficient (R) measures the strength of linear relationship between satellite and gauge rainfall. It is given by the equation

\[
R = \frac{\sum_{i=1}^{n}(G_i - \bar{G})(S_i - \bar{S})}{\sqrt{\sum_{i=1}^{n}(G_i - \bar{G})^2} \sqrt{\sum_{i=1}^{n}(S_i - \bar{S})^2}}
\]

where \(G_i\) is gauge rainfall amount, \(\bar{G}\) mean gauge rainfall amount, \(S_i\) is satellite rainfall estimates, \(\bar{S}\) is mean satellite rainfall estimates, and \(n\) is total number of data.

The mean error (ME) defined by the equation

\[
ME = \frac{1}{n} \sum_{i=1}^{n} (S_i - G_i)
\]

![Figure 1](image-url) | The study area and the distribution of meteorological stations used for validation.

<table>
<thead>
<tr>
<th>Station ID</th>
<th>Name</th>
<th>Latitude (degree)</th>
<th>Longitude (degree)</th>
<th>Elevation (m)</th>
</tr>
</thead>
<tbody>
<tr>
<td>S1</td>
<td>Metema</td>
<td>12.775</td>
<td>36.414</td>
<td>790</td>
</tr>
<tr>
<td>S2</td>
<td>Chagni</td>
<td>10.974</td>
<td>36.499</td>
<td>1,614</td>
</tr>
<tr>
<td>S3</td>
<td>Wetet Abay</td>
<td>11.37</td>
<td>37.042</td>
<td>1,920</td>
</tr>
<tr>
<td>S4</td>
<td>Aykel</td>
<td>12.48</td>
<td>37.03</td>
<td>2,150</td>
</tr>
<tr>
<td>S5</td>
<td>Debre Tabor</td>
<td>11.867</td>
<td>37.995</td>
<td>2,612</td>
</tr>
<tr>
<td>S6</td>
<td>Felege Berhan</td>
<td>10.743</td>
<td>38.067</td>
<td>2,710</td>
</tr>
<tr>
<td>S7</td>
<td>Rebu Geeya</td>
<td>10.548</td>
<td>37.767</td>
<td>2,958</td>
</tr>
<tr>
<td>S8</td>
<td>Kimir Dingay</td>
<td>11.814</td>
<td>38.217</td>
<td>2,980</td>
</tr>
</tbody>
</table>
is the measure of average difference between satellite and gauge rainfall amounts. A positive value reflects an overestimation of satellite rainfall whereas negative value indicates underestimation of satellite rainfall.

The mean absolute error (MAE) measures the average magnitude of the absolute value difference between satellite and gauge rainfall amounts. It is calculated using the formula

$$\text{MAE} = \frac{1}{n} \sum_{i=1}^{n} |S_i - G_i|$$  \hspace{1cm} (3)

Percent bias (PB) measures the average tendency of estimated values, which can either be larger or smaller than their observed ones, with an optimal value of 0. It can be calculated by

$$\text{PB} = \frac{\sum_{i=1}^{n} (S_i - G_i)}{\sum_{i=1}^{n} G_i} \times 100$$ \hspace{1cm} (4)

Rainfall variability and trend

The annual, seasonal, and monthly CHIRPS rainfall time series for the period of 1981–2017 were used to analyze the spatial and temporal variability of rainfall and to test its trend. The rainfall seasons for the Amhara region are identified as follows: the winter season comprises December–January–February (DJF), spring from March to May (MAM), summer includes June–July–August (JJA), and autumn from September to November (SON). A number of techniques have been developed for the variability and trend analysis of the rainfall time series. Variability analysis involves the use of coefficient of variation (CV), standardized anomaly index (SAI), precipitation concentration index (PCI), moving average and seasonality index (SI). Trend detection and analysis can be performed through parametric and non-parametric tests. Parametric tests are more powerful but they require the data to be normally distributed, which is rarely true for climatic and hydrological data that are usually skewed, and may contain outlier observations (Yue et al. 2002). On the other hand, non-parametric statistical tests are not affected by the actual distribution of data and are less sensitive to outliers (Yue et al. 2002). One of the most widely used non-parametric tests for detecting a trend in hydro-climatic time series is the Mann–Kendall (MK) test (Douglas et al. 2000). Thus, in this study, rainfall variability has been computed using CV, SAI, PCI, and SI. Moreover, MK test and Sen’s slope estimator were applied to detect and quantify possible trends in the time series data.

Coefficient of variation

The coefficient of variation measures the overall variability of the rainfall in the area of interest. A higher value of CV indicates a rainfall greater variability and vice versa. It is computed using the formula

$$\text{CV} = \frac{\sigma}{\mu} \times 100$$  \hspace{1cm} (5)

where $\sigma$ is the standard deviation and $\mu$ is the mean rainfall for the chosen temporal scales. Generally, CV is used to classify the degree of variability of rainfall events into three: low ($\text{CV} < 20$), moderate ($20 < \text{CV} < 30$), and high ($\text{CV} > 30$) (Asfaw et al. 2012).

Standardized anomaly index

Standardized anomaly index of rainfall has been calculated to examine the nature of the trends. It enabled the determination of the dry and wet years in the record and is used to assess frequency and severity of droughts and it is computed as:

$$\text{SAI}_i = \frac{X_i - \bar{X}}{\sigma}$$ \hspace{1cm} (6)

where $X_i$ is the annual rainfall of the particular year; $\bar{X}$ is the long-term mean annual rainfall over a period of observation and $\sigma$ is the standard deviation of annual rainfall over the period of observation. Negative values indicate a drought period as compared to the chosen reference period while the positive ones indicate a wet situation. SAI is also computed for seasonal scale. SAI value classification is presented in Table 2.

Rainfall seasonality

To evaluate seasonality of rainfall, PCI and SI were used. The PCI indicates the distribution of monthly rainfall and
can be used as an indicator of hydrological hazard risks such as floods and droughts (Gocic et al. 2016). PCI was calculated on an annual scale for each grid point according to the equation

$$PCI = \frac{\sum_{i=1}^{12} P_i^2}{\left(\sum_{i=1}^{12} P_i\right)^2} \times 100 \hspace{1cm} (7)$$

where $P_i$ is the monthly precipitation in month $i$.

Oliver (1980) suggested that PCI value <10 represents a uniform precipitation distribution; PCI values from 11 to 15 show moderate rainfall concentration; values from 16 to 20 indicate an irregular distribution; and values above 20 represent a strong irregular precipitation distribution.

SI is an index which helps to identify the rainfall regimes on the monthly distribution of rainfall. Moreover, this index quantifies the degree of variability in monthly rainfall through the year. The higher the seasonality index of a region the greater the water resource variability and scarcity in time, the more vulnerable the area to desertification. SI is simply the sum of absolute deviations of mean monthly rainfall from the overall monthly mean, divided by the mean annual rainfall. The computation of SI is done using the formula

$$SI = \frac{1}{P} \sum_{i=1}^{12} \left| P_i - \frac{P}{12} \right| \hspace{1cm} (8)$$

where, $P_i$ is the mean rainfall (mm) of the $i^{th}$ month, and $P$ is the mean annual rainfall (mm). The index varies from zero, if all the months have equal rainfall, to 1.83 if all the rainfall occurs in a single month. Table 3 shows the different class limits of SI and representative rainfall regimes (Kanellopoulou 2002).

### Serial autocorrelation test

In order to avoid the influence of serial autocorrelation on the MK trend test, the serial autocorrelation should be checked before applying the MK trend test. To check the presence of a significant autocorrelation, correlograms and autocorrelation function (ACF) at lag 1 were used. Lag 1 ACFs were computed using the formula

$$r_1 = \frac{1}{n-1} \sum_{i=1}^{n-1} (X_i - \bar{X})(X_{i+1} - \bar{X}) \div \left[ \frac{1}{n} \sum_{i=1}^{n} (X_i - \bar{X})^2 \right] \hspace{1cm} (9)$$

where $r_1$, $X_i$ and $\bar{X}$ are the correlation coefficient at lag 1, rainfall time series, and mean value of the rainfall time series, respectively. The confidence interval of $r_1$ at the 5% significance level can be computed as

$$r_1(5\%) = \left( -1 \pm 1.96 \sqrt{n - 2} \right) / (n - 1) \hspace{1cm} (10)$$

If $r_1$ is found to be within the confidence limits, it can be concluded that the time series does not exhibit a significant autocorrelation and the MK test can be applied directly. On the contrary, if $r_1$ falls outside of the confidence interval, it can be said that the time series exhibits a significant autocorrelation at the 5% significance level and the MK test should be applied after the removal of the autocorrelation. Hamed & Rao (1998) proposed a modified Mann–Kendal (MMK) procedure that takes serial dependence into account. When serial dependence is absent, the MMK trend test is
less efficient than the original test (Naveendrakumar et al. 2018).

**Mann–Kendall (MK) test**

According to the MK test, this study tested the null hypothesis ($H_0$) of no trend, that is the observations $x_i$ are randomly ordered in time, against the alternative hypothesis ($H_1$), where there is a monotonic (increasing or decreasing) trend in the time series. The MK statistics $S$ is calculated using the formula

$$ S = \sum_{i=1}^{n-1} \sum_{i<i+1} \text{sgn}(x_j - x_i) $$

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

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

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

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

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 $t_i$ is number of data points in the $i^{th}$ group.

The $Z$ statistics is computed using the formula

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

A significant level $\alpha$ is also utilized for testing either an upward or downward monotone trend. The trend is significant at the 90% confidence level if $|Z| > 1.65$, at the 95% confidence level if $|Z| > 1.96$, and at the 99% confidence level if $|Z| > 2.58$ (Mandale et al. 2017). The positive and negative $Z$ values indicate increasing and decreasing trend, respectively.

**Sen’s slope estimator**

This study used Sen’s slope estimator to calculate the actual slope of time series data trends. If a linear trend exists, the magnitude of the monotonic trend in hydrologic time series can be quantified by using the nonparametric Sen’s estimator of slope using the following equation (Sen 1968)

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

where $\beta$ represents the median value of the slope values between data measurements $x_i$ and $x_j$ at the time steps $i$ and $j$ ($i < j$), respectively. Positive value of $\beta$ indicates an increasing trend whereas negative value of $\beta$ indicates a decreasing trend. The sign of $\beta$ reflects data trend direction, whereas its value indicates the steepness of the trend. The advantage of this method is that it limits the influence of missing values or the outliers on the slope in comparison with linear regression.

**RESULTS AND DISCUSSION**

**Validation results**

The performance metrics results of the comparisons between rain gauge measurements and CHIRPS data at both monthly and annual scales for the period 2000 to 2010 are shown in Table 4. Good agreement between the station observations and CHIRPS rainfall data was observed with correlation coefficients $R = 0.91$ and $R = 0.86$ for monthly and annual scales, respectively. The negative

<table>
<thead>
<tr>
<th>Temporal scale</th>
<th>$R$ [fraction]</th>
<th>ME [mm]</th>
<th>MAE [mm]</th>
<th>PB [%]</th>
</tr>
</thead>
<tbody>
<tr>
<td>Monthly</td>
<td>0.91</td>
<td>-2.27</td>
<td>32.73</td>
<td>-1.97</td>
</tr>
<tr>
<td>Annual</td>
<td>0.86</td>
<td>-8.66</td>
<td>94.26</td>
<td>-0.62</td>
</tr>
</tbody>
</table>

Table 4 | Performance metrics of rainfall at monthly and annual scales for the stations and CHIRPS rainfall data from 2000 to 2010 in the study area
values of ME and PB in both temporal scales indicated that the CHIRPS data tended to slightly underestimate the observed rainfall data. In general, the performance metrics revealed that better agreement between rain gauge measurements and CHIRPS data was observed in the monthly scale than the annual scale, and further validation results were presented using the monthly scale.

In addition to performance metrics, Figure 2 shows the scatter plot of rain gauge observations and CHIRPS rainfall estimates at monthly scale for the 2000–2010 period. From the figure, it is evident that CHIRPS product revealed an overestimation of the low rainfall values and an underestimation of the high values. Generally, CHIRPS product showed a moderate overestimation of the observed amount of rainfall between 0 and 150 mm/month, whereas it tended to underestimate those values over 150 mm/month.

To evaluate the stability of CHIRPS rainfall product during the period 2000–2010, the performance metrics were computed for monthly scale for each year and the results are presented in Table 5. As can be seen from the table, ME and PB showed both negative and positive values for different years. The minimum MAE (22.66 mm) and maximum MAE (48.61 mm) were recorded in the years 2005 and 2009, respectively. The values of coefficient of correlation R ranged from 0.80 to 0.96. The overall evaluation of performance metrics, summarized in Table 5, revealed a good agreement between CHIRPS rainfall estimates and gauge observations and further implied the stability of CHIRPS data during the validation period.

To see the effects of elevation variability on the performance of CHIRPS rainfall estimates, stations with a broad range of elevations from 790 to 2,980 m a.s.l were used. The results of the performance metrics obtained by comparing rain gauge measurements and CHIRPS rainfall data for each station at monthly time scale are presented in Table 6. The correlation coefficients ranged from 0.88 to 0.94, indicating good agreement between CHIRPS rainfall estimates and rain gauge observations at both high and low elevations. Results of ME and PB revealed that CHIRPS rainfall estimates tended to underestimate rain gauge observations at low elevations. In general, from the values of R it can be inferred that CHIRPS product performed better at a low elevation.
elevation. However, in other performance metrics (ME, MAE and PB) no clear relationships between change in elevation and CHIRPS rainfall estimates were observed.

Overall, the results of this validation study have shown the potential of CHIRPS rainfall product to be used for various applications such as rainfall pattern and variability study in Amhara region.

Rainfall summary statistics

Rainfall characteristics, such as mean, standard deviation (SD), CV, and percentage contributions of monthly and seasonal rainfall to annual rainfall were computed for the period 1981 to 2017 over the study area and the results are presented in Table 7.

The mean annual rainfall was 1,110.81 mm with standard deviation 239.25 mm. August (287.4 mm) and July (284.3 mm) contributed the maximum share to the annual rainfall budget (25.87% and 25.59%, respectively) followed by September (12.59%) and June (10.74%). January and February received the least rainfall, and contributed 0.96% and 1.38% of the annual rainfall, respectively. The major share of the annual rainfall (>81%) was received in summer (JJA) and autumn (SON). The former contributed 62.21% and the latter contributed 19.15%. Spring (MAM) and winter (DJF) contributed 15.49% and 3.14%, respectively. The annual rainfall was significantly correlated with summer and autumn rainfall ($R = 0.87$ and 0.85, respectively; $p < 0.0001$). The spatial distribution of annual rainfall during the period of 1981–2017 is presented in Figure 3. From the figure, it can be seen that the highest rainfall values were recorded in the western part and the lowest values were recorded in the northeastern part of the study area.

The spatial distribution of rainfall for all seasons is shown in Figure 4. During winter (DJF), the southeastern part of the study area received maximum rainfall while the northern and northwestern parts of the study area received low rainfall. Similarly, during MAM, the highest rainfall was observed in the southeastern and southwestern parts of the region. JJA and SON almost followed the same spatial distribution of rainfall with that of the annual rainfall.

<table>
<thead>
<tr>
<th>Month</th>
<th>Mean [mm]</th>
<th>SD [mm]</th>
<th>CV [%]</th>
<th>Z value</th>
<th>Sen’s slope ($\beta$)</th>
<th>Contribution to annual rainfall (%)</th>
</tr>
</thead>
<tbody>
<tr>
<td>Jan</td>
<td>10.72</td>
<td>8.09</td>
<td>75.47</td>
<td>−0.33</td>
<td>−0.02</td>
<td>0.96</td>
</tr>
<tr>
<td>Feb</td>
<td>15.33</td>
<td>9.53</td>
<td>62.17</td>
<td>−1.53</td>
<td>−0.15</td>
<td>1.38</td>
</tr>
<tr>
<td>Mar</td>
<td>37.8</td>
<td>21.77</td>
<td>57.59</td>
<td>−1.01</td>
<td>−0.21</td>
<td>3.4</td>
</tr>
<tr>
<td>Apr</td>
<td>52.66</td>
<td>33.73</td>
<td>64.05</td>
<td>−0.46</td>
<td>−0.11</td>
<td>4.74</td>
</tr>
<tr>
<td>May</td>
<td>81.62</td>
<td>32.63</td>
<td>39.98</td>
<td>1.35</td>
<td>0.76</td>
<td>7.35</td>
</tr>
<tr>
<td>Jun</td>
<td>119.3</td>
<td>38.81</td>
<td>32.53</td>
<td>0.41</td>
<td>0.15</td>
<td>10.74</td>
</tr>
<tr>
<td>Jul</td>
<td>284.3</td>
<td>70.24</td>
<td>24.71</td>
<td>1.37</td>
<td>1.31</td>
<td>25.59</td>
</tr>
<tr>
<td>Aug</td>
<td>287.4</td>
<td>48.01</td>
<td>16.7</td>
<td>0.93</td>
<td>0.66</td>
<td>25.87</td>
</tr>
<tr>
<td>Sep</td>
<td>139.9</td>
<td>51.63</td>
<td>36.9</td>
<td>0.41</td>
<td>0.19</td>
<td>12.59</td>
</tr>
<tr>
<td>Oct</td>
<td>58.08</td>
<td>32.21</td>
<td>55.46</td>
<td>0.25</td>
<td>0.11</td>
<td>5.23</td>
</tr>
<tr>
<td>Nov</td>
<td>14.82</td>
<td>7.83</td>
<td>52.83</td>
<td>1.78*</td>
<td>0.10</td>
<td>1.33</td>
</tr>
<tr>
<td>Dec</td>
<td>8.88</td>
<td>5.21</td>
<td>58.67</td>
<td>−0.43</td>
<td>−0.02</td>
<td>0.8</td>
</tr>
<tr>
<td>Annual</td>
<td>1,110.81</td>
<td>239.25</td>
<td>21.53</td>
<td>1.45</td>
<td>0.19</td>
<td>100</td>
</tr>
<tr>
<td>MAM</td>
<td>172.1</td>
<td>65.12</td>
<td>37.84</td>
<td>0.56</td>
<td>0.13</td>
<td>15.49</td>
</tr>
<tr>
<td>JJA</td>
<td>691.1</td>
<td>134.02</td>
<td>19.39</td>
<td>1.61</td>
<td>0.79</td>
<td>62.21</td>
</tr>
<tr>
<td>SON</td>
<td>212.8</td>
<td>72.45</td>
<td>34.05</td>
<td>0.80</td>
<td>0.15</td>
<td>19.15</td>
</tr>
<tr>
<td>DJF</td>
<td>34.93</td>
<td>18.19</td>
<td>52.08</td>
<td>−1.37</td>
<td>−0.07</td>
<td>3.14</td>
</tr>
</tbody>
</table>

The Sen’s slope ($\beta$) is given in mm/month, mm/year, and mm/season for monthly, annual, and seasonal time scales, respectively.

*Significant at 0.1 level.
Variability and anomalies of rainfall between 1981 and 2017

The coefficient of variation of the annual rainfall (21.13%) revealed moderate inter-annual variability of annual rainfall over the study area. Similarly, July and August had moderate rainfall variability (10 < CV < 30). The remaining months had coefficients of variation between 50% and 75%, indicating higher rainfall variability in these months. Similarly, higher rainfall variability was observed in all seasons except summer (JJA). Although annual rainfall showed moderate inter-annual variability, seasonal rainfall (except summer) showed comparably higher coefficient of variation, implying much larger variation in the seasonal rainfall between the years. Moreover, the CV of winter rainfall (52.08%) was higher than that of summer rainfall (19.39%), which implied more inter-annual variability of winter than summer. The result agreed with the findings of previous studies in most parts of Ethiopia (Seleshi & Camberlin 2006; Asfaw et al. 2018). Such seasonal and inter-annual variability in rainfall amount could negatively affect the ability of farmers to mitigate the effects of climate change and variability (Ayalew et al. 2012).

The spatial distribution of the coefficient of variation of the annual rainfall in the study area is shown in Figure 5. The CV varied from 6.42% in the southwestern part of the study area to 20.18% in the northeastern part of the study area. Areas with high annual rainfall indicated less inter-annual variation whereas areas with low annual rainfall showed moderate inter-annual variation. The moderate inter-annual variability in low rainfall areas indicated that comparably there was a greater contrast in annual rainfall values from year to year, and it suggested that in such areas, water availability became somehow more unpredictable as compared to areas with low CV.

Figure 6(a)–6(d) show the spatial distributions of the CV of seasonal rainfall in the study area. As compared to annual rainfall, seasonal rainfall was characterized by high inter-annual variability up to 234% with DJF rainfall. The CV in JJA rainfall (8.23 % < CV < 37.32 %) appeared relatively stable compared to the remaining seasons. Generally, results of CV of seasonal rainfall revealed variable spatial and temporal trends in the study area. Maximum CV in DJF rainfall was observed in the northwestern and northeastern parts of the area, whereas in SON rainfall, the maximum CV was observed in the eastern and southern parts. Similarly, in MAM and JJA, the highest values of the coefficient of variation were observed predominantly in the northern and eastern parts, respectively.

Figure 7 shows the annual rainfall anomalies over Amhara region from 1981 to 2017. The rainfall anomalies showed the presence of inter-annual variability of rainfall and the percentages of negative and positive anomalies were 59.46% and 40.54%, respectively. The highest positive anomaly (0.57) was observed in the year 1998 whereas the highest negative anomaly (−1.07) was observed in the year 1984. The negative anomalies became more pronounced particularly in the 1980s, in the early 1990s, and in the early 2000s, which correlated with the historic drought years in the country (Suryabhagavan 2017). Similarly, the results of the SAI analysis of seasonal rainfall of the region during the study period are shown in Figure 8. During the study period, the percentage of negative anomalies exceeded that of the positive anomalies in all seasons except summer. Like annual rainfall, inter-annual variability of rainfall was observed in MAM, JJA, SON, and DJF with negative anomalies in 64.86%, 48.65%, 64.86%, and 59.46% of the
Figure 4 | Spatial distribution of seasonal rainfall (mm) of the Amhara region (1981–2017): (a) winter (DJF), (b) spring (MAM), (c) summer (JJA), and (d) autumn (SON).
analyzed years, respectively. The highest positive anomaly (1.36) was observed in MAM in the year 2014 whereas the highest negative anomaly (−1.54) was observed in JJA in the year 2015. DJF season shows a predominance of negative anomalies starting from 1993, the results of which are coherent with the negative trend (Table 7), even without the support of the significance.

Rainfall seasonality

Figure 9 presents the spatial distribution of the mean PCI of annual rainfall of the Amhara region from 1981 to 2017. As shown in the figure, PCI varied from 14.59 to 25.60. Maximum values of PCI were observed in the northeastern parts of the study area whereas the minimum values of PCI were observed predominantly in the southwestern part of the study area.

Table 8 shows the area (in percentage) of the different classes of PCI of the study area. From the table, we can understand that 0.44% of the study area had moderate rainfall distribution, 34.56% of the area had irregular rainfall distribution, and the majority of the study area (65%) was characterized by strong irregular rainfall distribution.

Figure 10 illustrates the spatial distribution of SI in the Amhara region. The minimum SI values (0.64) were observed in the southeastern part of the study area whereas the maximum values (1.14) were observed in the north and northwestern parts of the study area.

The area (in percentage) of the different classes of SI of the study area is presented in Table 9. As observed in the table, 26.13% of the study area showed seasonal rainfall (mean SI values between 0.60 and 0.79). The majority of the study area (63.19%) was characterized by markedly seasonal rainfall with a long drier season (SI values from 0.80 to 0.99), whereas the remaining 10.68% of the study region got rainfall in three months or less.

Generally, the rainfall seasonality derived from mean PCI and SI showed an almost similar geographic pattern with high spatial variability. More pronounced rainfall seasonality was observed as we go from the southern to the northern parts of the study area. Correlation analysis was performed to ascertain the effects of geographic coordinates on the seasonality indices. The geographic coordinates of the centers of each pixel and the corresponding pixel values of the raster images (of PCI and SI) were extracted using the Spatial Analyst Extension Tool of ArcGIS. Further, Pearson correlation coefficients between the extracted geographic coordinates and the corresponding values of PCI and SI were computed. The results are presented in Table 10. As can be seen from the table, both PCI and SI are positively correlated to latitude with correlation coefficients 0.41 and 0.62, respectively. On the other hand, the correlations between PCI and SI with longitude are positive (0.13) and negative (−0.56), respectively.

Trend analysis results

Examination of the autocorrelation function for annual rainfall time series did not reveal any significant serial correlation at all lags at the 95% confidence limit (Figure 11), enabling MK test to be applied without any further modifications. Following the serial correlation test, the MK test and Sen’s slope estimator were applied to the rainfall time series data from 1981 to 2017 for Amhara region.

The trend analysis results, including the Z value from the MK test and the trend’s slope (β) from Sen’s estimator are
Figure 6 | Spatial distribution of CV of the seasonal rainfall of the Amhara region (1981–2017): (a) winter (DJF), (b) spring (MAM), (c) summer (JJA), and (d) autumn (SON).
presented in Table 7. The results of MK test for monthly rainfall data revealed a statistically significant increasing trend for the month of November at 10% level of significance. Non-significant increasing trend was observed for the months May, June, July, August, September, and October. The remaining months have a non-significant decreasing trend. The highest positive rate of change (1.31 mm/year) was observed in the month of July (although it was statistically insignificant). Generally, the large percentage of detected trends in monthly rainfall was positive (58.33%) rather than negative (41.67%). A statistically non-significant increasing trend was observed for summer, spring, and autumn rainfall at 10% significance level. On the other hand, winter had a non-significant decreasing trend. The annual rainfall has shown a non-significant increasing trend at 10% significance level. Other studies in different parts of...
Ethiopia also did not find a statistically significant trend in the annual rainfall (Viste et al. 2013; Mengistu et al. 2014). The spatial distribution of Sen’s slope for annual rainfall is presented in Figure 12. As depicted in the figure, annual rainfall in Amhara region showed an increasing trend in most parts of the region. Only small sections in the northern and southeastern parts of the region revealed decreasing trend in annual rainfall.

**CONCLUSIONS**

The availability of high spatial and temporal resolution satellite-derived rainfall products at local and global scales has proved to be valuable in complementing ground-based datasets, especially in developing countries that have data scarcity. This study has presented a detailed analysis of the spatial and temporal variability and monotonic trends of rainfall in Amhara region using CHIRPS rainfall data for a period of 37 years (1981–2017). The mean annual rainfall of the region was 1,110.81 mm with standard deviation...
and coefficient of variation 239.25 mm and 21.13%, respectively. The coefficient of variation of the annual rainfall revealed moderate inter-annual variability of annual rainfall over the study area. However, much larger variation was observed in the seasonal rainfall between the years. Results of standardized anomaly index showed that the percentage of negative anomaly (59.46%) surpassed that of the positive anomaly (40.54%) during the study period. The PCI and SI maps showed almost similar geographic pattern. The PCI varied from 14.59 to 25.60, where highest values were observed in the southwestern parts of the study area, whereas the SI varied from 0.64 to 1.14. From the analysis of these indices (PCI and SI), it can be inferred that most of the study area was characterized from seasonal to high seasonal rainfall distribution with longer drier season. The trend analysis presented both downward and upward trends depending on the chosen temporal scales. There was an overall increase in the annual and seasonal rainfall (except winter) in the study area during the study period. The present study has offered useful information to better understand the spatial distribution and temporal trends of rainfall in the study area, which is of great importance for management of water resources and securing sustainable agricultural production. However, more comprehensive study on the driving forces of the trends and better validation options are required in the future.

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