Impact of rainfall variability on crop yields and its relationship with sea surface temperature in northern Ethiopian Highlands

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Abstract
Knowing the spatial and temporal variation of rainfall is crucial for the management of agricultural productivity. This study aimed at evaluating rainfall variability impact on crop yields and its relationship with sea surface temperature using GIS and statistical techniques in North and South Wello zones, northern Ethiopian Highlands. In this study, 30 years (1984–2013) time series data of rainfall from National Centers for Environmental Prediction’s Climate Forecast System Reanalysis and National Meteorological Agency, sea surface temperature from National Oceanic and Atmospheric Administration, and crop data from Central Statistical Agency were used. With regard to spatial and temporal distribution of rainfall, the highest amount of mean total Kiremt/summer and annual rainfall was 993.71 mm and 1715.95 mm, respectively. The magnitude of mean total Kiremt and annual rainfall temporal and spatial variations, using percentage of coefficient variation, was ranging from 24.8 to 62% and from 23.13 to 57.86%, respectively. The correlation between total Kiremt and Belg rainfall with mean sea surface temperature was negative ($r = -0.457$) and positive ($r = 0.385$), respectively and statically significant at alpha 0.05 level. From the regression analysis, it was observed that the variation of crop production was explained by the variation of rainfall. For instance, the impact of mean Kiremt rainfall accounted for 47.5% ($R^2 = 0.475$) of variations in sorghum. Generally, the analysis of this study revealed that rainfall variability is one of the major determinant factors for variation of major crop yields in the study area, and this information might be used as an input for decision-makers take appropriate adaptive measures in various agricultural and water resource sectors. For instance, this study recommends the expansion of irrigation and water management practice and promoting perennial trees like fruits and drought-resistant crops.

Keywords Rainfall variability · Sea surface temperature · Crop yields · Spatial distribution of rainfall · Coefficient of variation

Introduction
Today, climate variability is increasingly recognized as a critical challenge to ecological health, human well-being, and future development. It is the most serious challenge that humanity may ever face. Hence, it has recently become a pressing issue in various development, environment, and political forums at national, regional, and international levels (Mikias, 2014). Among the basic climatic elements, rainfall shows seasonal and annual variation different from normally expected climatic conditions. In the Sub-Saharan Africa, climate change has drastically reduced agricultural production through extreme weather events, such as recurrent droughts and floods (Nhemachena and Hassan, 2007). Even though climate change is global in nature, potential changes are not expected to be globally uniform; rather, there may have dramatic regional differences (Mulugojjam and Ferede, 2012).

Different studies have shown the importance of climate variability in explaining crop production fluctuations at different spatial scales. At the global level, estimates are that climate variability accounts for roughly a third of observed crop yield variability (Ray et al., 2015). At the continental level, climate variability is widely recognized to be a major driver of crop production fluctuations particularly in Africa, where agriculture is predominantly small scale and rain-fed (Jones and Thornton, 2003; IPCC, 2014). For instance, Rowhani (2011) and Afifi et al. (2014) reported that annual variability of rainfall and temperature had significant impacts on crop production and thereby food security of communities in Tanzania. In
Nigeria, rainfall variability was found to have a significant influence on crop production (Adamgbe and Ujoh, 2013; Akinseye et al., 2013; Yamusa et al., 2015). In Uganda, variations in rainfall and temperature had significant effects on crop production (Mwaura and Okoboi, 2014).

In Ethiopia, climate is influenced by general atmospheric and oceanic factors that affect the weather condition and the time of inception and intensity of the rains (Bekele, 1993). The summer rainfall contributes about 74% of the annual rainfall in the country. Therefore, the failure of the summer rainfall has disastrous consequences upon the country and the rest of east Africa (Robel, 2012). The failure of seasonal rainfall adversely affects the country’s socio-economy, in particular food production (Babu, 1999). Variability of rainfall is believed due to variations of tropical oceanic and atmosphere interaction, especially El Niño-Southern Oscillation (ENSO) (Haile, 1988).

The National Meteorological Service Agency (NMSA) of Ethiopia assured that ENSO is strongly related to rainfall distribution in the country (Babu, 1999). Researchers at NMSA and policy makers in Ethiopia stated that the state of sea surface temperatures (SST) in the tropical Pacific Ocean affect Ethiopian climate through teleconnections (Haile, 1988). National Meteorological Services Agency [NMSA], 2001 also explained that the Atlantic and the Indian oceans’ SST anomalies (SSTA) affect Ethiopian climate (Robel, 2012). Quinn (1992) also reported that the variability between high and low flood levels of the Nile River, whose major water source is highlands of Ethiopia, is related to the ENSO.

Previous investigations revealed that El Niño/Southern Oscillation (ENSO) has a great influence on rainfall variability in Ethiopia (Lyon 2014; Seneshaw and Yitea 2015; Alhamshry et al. 2020). During El Niño (La Niña), precipitation in equatorial east Africa might be positively or negatively affected by easterly (westerly) wind anomalies (Ratnam et al. 2014). ENSO is the inter-annual fluctuation of the atmosphere-ocean system in the equatorial Pacific and it has three phases: warm (El Niño), cold (La Niña), and neutral (Chen et al. 2014; Jajca ye et al. 2018; FAO, 2019). Neutral conditions occur when neither El Niño nor La Niña is present (FAO 2019). El Niño is a recurrent global atmospheric oceanic phenomenon associated with an increase in SST in the central tropical Pacific Ocean. It boosts the risk of heavy rainfall and flooding in some parts of the world and the risk of drought in some parts (FAO, 2019). The SST of the tropical Pacific shows a discrepancy both spatially and temporally (Philip 2018) and a very high correlation exists between precipitation and SST (Pegion and Kirtman 2008; Wu et al. 2008; Chen et al. 2014).

In Ethiopia, El Niño has been the cause of crop failure, livestock death, and food insecurity for many years. Analyzing El Niño/La Niña Southern Oscillation episodes together with other climatic parameters would be helpful for many sectors. El Niño originates in the Eastern Pacific, but its warming effect is rapidly spread by the winds that blow across the ocean altering the weather patterns in more than 60% of the planet’s surface. In Ethiopia, the El Niño has been the cause of crop failure, livestock death, food insecurity, and others problems for many years (Getahun and Shefne, 2015). Therefore, analyzing spatial and temporal variability of rainfall, its impact on crop yields, as well as its relationship with sea surface temperature would have great scientific importance. As to the knowledge of the researcher, studies relating to sea surface association with rainfall and temperature have not been still conducted in the study area. Basically, the investigator was necessitated to conduct this study primarily to fill the gap that had not discussed by previous researchers and provide a cumulative knowledge in the area by incorporating the issue of GIS and statistical techniques.

Materials and methods

Study area description

This study was conducted in the North and South Wello zones in the Amhara National Regional State, Ethiopia. The zones are located in the eastern part of the region. The capitals of the South and North Wello zones are Dessie and Weldia, respectively. Dessie and Weldia are about 410 km and 521 km north of the Ethiopian capital, Addis Ababa, respectively. The two zones are located between 10°12′ to 12°22′ N latitude and 38°30′ to 40°14′ E longitude and cover about 30,000 km² (Fig. 1).

Data type and sources

The data used for this study were rainfall found from the National Centers for Environmental Prediction’s Climate Forecast System Reanalysis (CFSR) and Ethiopian National Meteorological Agency (NMA). In addition, Central Statistical Agency (CSA) time series data on production of five major crops: barley (Hordeum vulgare), maize (Zea mays), sorghum (Sorghum bicolor), teff (Eragrostis tef), and wheat (Triticum aestivum) grown in the area for the main cropping season, locally known as Meher (any temporary crop harvested between September and February), have been employed. Therefore, weather data sources used were observed weather data from climatic stations in the study area (hereafter called “ground meteorological stations”) and weather data from the NCEP’s CFSR (hereafter called “CFSR weather”) (Saha et al., 2010). Another variable used in this research was sea surface temperature (SST) obtained from National Oceanic and Atmospheric Administration (NOAA) satellite mission.
The ground meteorological stations have monthly rainfall from five climatic stations. It spans the period from 2000 to 2016 inclusive. However, spatial location of these stations that record rainfall data was distributed unevenly and there were data gaps in the study area. In addition to this, the numbers of ground meteorological stations found in the study area were unsatisfactory and the period of record does not include adequate historical coverage to analyze rainfall variability. Therefore, the present study used CFSR weather data instead of using in situ rainfall data from NMA.

Many studies have explored ways to improve the quality of climatic data in data-scarce regions. Barrett (1994) and Tsintikidis et al. (1999) have applied satellite as weather data inputs. Others have employed various statistical methods to fill data gaps. Tesemma et al. (2009) used regression and spatial interpolation to fill data gaps. While these are some of the various efforts exerted to improve climatic data quality in data limited regions, CFSR data sources are becoming very promising options in representing observed weather data (Zhang et al., 2012).

It is not always easy to find weather data from ground meteorological stations at a given spatial and temporal resolution, especially in this study area. Moreover, when the data exist, they may be unreliable because of gaps and other problems, such as random errors. In such cases, it may be better to use global data sources such as CFSR. CFSR weather has an advantage over ground meteorological stations weather data in that it provides complete sets of climatic data (Dile and Raghavan, 2014).

The CFSR weather is an open global reanalysis dataset for each hour at 38-km resolution (Fuka et al., 2013). For this research CFSR weather data were obtained by bounding box of latitude 8.6896°S, longitude 36.0956°W, latitude 13.3148°N, and longitude 40.2045°E (the Texas A&M University spatial sciences website, globalweather.tamu.edu). It includes daily rainfall, maximum and minimum temperature, wind speed, relative humidity, and solar radiation from 1/1/1979 to 31/7/2014 for 195 locations. The CFSR weather is produced using cutting-edge data-assimilation techniques (both data from ground meteorological stations and satellite irradiances) as well as highly advanced (and coupled) atmospheric, oceanic, and surface-modeling components at ~38-km resolution (Saha et al., 2010). The production of CFSR data involves various spatial and temporal interpolations of ground meteorological stations of weather data found on the study area, other nearby data of ground meteorological stations, and satellite products (Dile and Raghavan, 2014). From 195 locations, 19 CFSR weather data stations were used in this study since they have appropriate distribution and long-term rainfall data from 1984 to 2013 in the study area.
Mean sea surface temperature (SST) of NINO3.4, NINO3, and NINO4 regions from National Oceanic and Atmospheric Administration (NOAA) satellite mission was used for the analysis to characterize the relationship between SST and rainfall in the study area. Since NINO 3.4 has characteristics of both NINO3 and NINO4 (Zaroug, 2010), NINO3.4 SST was considered in this study. To be classified as a full-fledged El Niño and La Niña episode the Oceanic Niño Index (ONI), sea surface temperature anomaly (SSTA) must exceed +0.5 (El Niño) or −0.5 (La Niña) for at least five consecutive months (Yitea, 2012).

Zonal level data on crop production were collected from the Central Statistical Agency for the period 2004–2015 inclusive, for which relatively good quality data were available. The short rainy season, Belg season, production was not included in this study for two reasons: its contribution to the annual total is not significant and it is much less than its national average contribution and the Belg season crop production data were not available on consecutive year in the study area.

### Estimating missing values using simple linear regression model

Time series is a sequential set of data measured over time. Thus, a set of data depending on time is called a time series; in this study, sea surface temperature and rainfall from 1984 to 2013 represent the time series. The analysis of time series data constitutes an important area of statistics (AfSar et al., 2013). Since the data records are taken through time, missing observations in time series data are very common. This occurs because an observation may not be made at a particular time owing to faulty equipment, lost records, or a mistake, which cannot be rectified until later. When one or more observations are missing, it is necessary to estimate the missing values from past-observed values by applying simple linear regression. By including estimated missing values, a better understanding of the nature of the data is possible with more accurate result of the analysis to achieve the stated objectives in this study.

Simple linear regression analysis describes the estimation of the unknown (missing) value of one variable from the known value of the other variable. There are two types of variables in simple linear regression analysis first tell us that the variable whose value is influenced or is to be predicted is called the dependent variable and the variable which influences the values or is used for prediction is called independent variable. Therefore, simple linear regression is the measure of the average relationship between two or more variables in terms of the original units of the data (AfSar et al., 2013).

As described in the previous section, CFSR weather data includes daily rainfall from 1/1/1979 to 31/7/2014. Daily data were converted to monthly data using excel spreadsheet since monthly data were required to achieve the study objectives. However, there were missing values from 2014 to 2016 inclusive. Therefore, simple linear regression equation from 1984 to 2013 was employed as a model to estimate missing values of for all months from 2014 to 2016 (Table 1). Simple linear regression model is expressed as:

\[ Y = a + bX \]  

where \( Y \) is the response/estimated value rainfall, \( X \) is explanatory variable (observation period), \( a \) is the intercept (the point where the line meets the Y-axis, where \( X = 0 \)), and \( b \) is the slope (gradient) of the line also called the regression coefficient. If \( b \) positive means, an increase in \( X \) leads to an expected increase in response variable \( Y \) and negative in \( X \) means, an expected decrease in response variable \( Y \)(AfSar et al., 2013).

### Validation of CFSR climate data

As described in the “Data type and sources” section, the CFSR weather is produced using cutting-edge data-assimilation techniques (both data of ground meteorological stations and satellite irradiances) as well as highly advanced (and coupled) atmospheric, oceanic, and surface-modeling components at ~38-km resolution (Saha et al., 2010). This indicates that the production of CFSR data involves various spatial and

### Table 1: Regression equations of each station to estimate missing values of rainfall

| CFSR Stations | Equations Rainfall          |
|---------------|-----------------------------|
| GW1           | \( Y = 152.86 - 0.22X \)   |
| GW2           | \( Y = 97.29 + 0.045X \)   |
| GW3           | \( Y = 28.63 - 0.005X \)   |
| GW4           | \( Y = 48.55 - 0.72X \)    |
| GW5           | \( Y = 100.88 - 0.141X \)  |
| GW6           | \( Y = 78.93 - 0.033X \)   |
| GW7           | \( Y = 35.26 - 0.0168X \)  |
| GW8           | \( Y = 72.36 - 0.12X \)    |
| GW9           | \( Y = 48.92 - 0.074X \)   |
| GW10          | \( Y = 19.52 - 0.023X \)   |
| GW11          | \( Y = 91.52 - 0.065X \)   |
| GW12          | \( Y = 137.31 - 0.14X \)   |
| GW13          | \( Y = 73.41 - 0.064X \)   |
| GW14          | \( Y = 16.40 + 0.021X \)   |
| GW15          | \( Y = 76.21 + 0.094X \)   |
| GW16          | \( Y = 172.62 - 0.128X \)  |
| GW17          | \( Y = 22.49 - 0.053X \)   |
| GW18          | \( Y = 24.39 - 0.020X \)   |
| GW19          | \( Y = 110.92 - 0.025X \)  |

Note: GW, global weather stations on the study area.
temporal interpolations of ground meteorological stations of weather data presented on the study area, other nearby ground meteorological stations weather data, and satellite products. It is uncertain whether this process would yield similar climatic results to the ground meteorological stations weather data, which is one reason for this validating assessment using meteorological gauge stations. Comparison of climate data (rainfall) from CFSR is done usually with ground meteorological stations data because it measures climate data directly.

The relationship of mean annual CFSR rainfall data with mean annual ground meteorological stations rainfall data could be studied by applying statistical analysis, correlation, to see how well the two data sets were associated for the stations. Correlation is commonly used in research and measurement studies, including studies conducted to obtain validity and reliability evidence (Goodwin and Leech, 2006). For comparison of CFSR data with the gauge data, five ground meteorological stations for rainfall, which have a smaller number of missing value and continuous record compared to the other stations for the period of 2000–2013, were used in this study. The spatial coverage of gauge and CFSR stations used for this work are distributed as shown in Figure 2. Stations of the two data sets which have higher proximity to each other were correlated to evaluate the relationship between the CFSR and ground meteorological stations data set.

The average value for annual CFSR rainfall and the corresponding gauged average annual rainfall were taken to test the reliability of the CFSR climate data. The results of correlation of CFSR rainfall with ground meteorological stations of rainfall observations for the period of 14 years from 2000 to 2013 inclusive are shown in Table 2. It shows the correlation coefficient ($r$) and $p$ value for testing the statistical significance of correlation between the two weather data sets. From correlation analysis, it was observed that the correlation of mean annual rainfall and temperature (both maximum and minimum) between the two weather data sources were positive, high, and statistically significant at $p$ value 0.01 level in all stations, indicating that CFSR weather data were of good quality to analyze climatic variability and trends in the study area. As to this analysis, similar results, Dile and Raghavan, 2014) evaluated the performance of CFSR climate data using ground meteorological stations gauge data. This implied that CFSR weather could be a valuable option to use in this study area where ground meteorological stations gauges are not available.

### Spatial interpolation by ordinary kriging

Sample data can provide valuable information, but due to many constraints, it is difficult to get the whole region sample data. Therefore, geo-statistical models predict the value in unsampled location and quantify the uncertainty of prediction.

Geo-statistical interpolation method, ordinary kriging, was employed in this study to generate surface maps for rainfall of the study area and to examine specific sample points to obtain a value for spatial autocorrelation that is only used for estimating around that particular point, rather than weighting nearby data points by some power of their inverted distance (IDW) which depends solely on distance to the prediction location. Ordinary kriging is one of the best estimation approaches of weather conditions at unsampled location in which the region is large and limited low density of base stations where the distribution of the station is unrepresentative of topographic variability and geographic features (Hunter and Meentemeyer, 2005). Ordinary kriging is an effective spatial interpolation

![Fig. 2 Geographical extent of El Niño regions](image)
and mapping tool, because it honors data locations, provides unbiased estimates at unsampled locations, and provides for minimum estimation variance, i.e., a best linear unbiased estimator (Getahun and Shefne, 2015). With the ordinary kriging method, the weights are based not only on the distance between the measured points and the prediction location but also on the overall spatial arrangement of the measured points.

\[ Z(\hat{s}_i) = \sum_{i=1}^{N} \lambda_i Z(s_i) \]  

(2)

where \( Z(s_i) \) is the measured or computed value (in this case rainfall) at \( i \)th location, \( \lambda_i \) is an unknown weight for the measured value at the \( i \)th location, \( \hat{s}_i \) is the prediction location, and \( N \) is the number of locations where rainfall values were measured.

**Correlation analysis**

Correlation and regression techniques are important in showing the relationship between climatic parameters and crop production and to identify the most predictor variable. Tunde et al. (2011), Rowhani (2011), Adamgbe and Ujoh (2013), and Akinseye et al. (2013) used the same methodology in their study of the relationship between climatic variables and crop production.

To determine the effect of climatic variables, namely, rainfall (monthly, seasonal, and annual rainfall totals) on crop production in the study area, coefficient of determination \( (R^2) \) from simple linear regression analysis was used. In addition to estimating missing values, regression analysis was also employed to quantify the influence of rainfall on crop yields per hectare.

To test the relationship between seasonal and annual rainfall with seasonal and annual sea surface temperature (SST), Pearson correlation was employed in this study area. The Pearson correlation coefficient \( (r) \) is a measure of the linear relationship between two variables \( X \) and \( Y \), giving a value between +1 and −1 inclusive, where 1 is total positive correlation, 0 is no correlation, and −1 is negative correlation. The strength of the correlation is not dependent on the direction or the sign. A positive correlation coefficient indicates that an increase in the first variable would correspond to an increase in the second, implying a direct relationship. A negative correlation indicates an inverse relationship. It is widely used in the science field as a measure of the degree of linear relationship between two variables (Guo et al., 2014). The absolute value of the correlation coefficients \( (r) \) was into a weak correlation \( (0 < |r| < 0.3) \), a low correlation \( (0.3 < |r| < 0.5) \), a moderate correlation \( (0.5 < |r| < 0.8) \), and a strong correlation \( (0.8 < |r| < 1) \) (Changbin et al., 2014). The mathematical formulation of Pearson correlation is presented as follows:

\[ r_{xy} = \frac{\sum_{i=1}^{n} (x_i - \bar{x})(y_i - \bar{y})}{\sqrt{\sum_{i=1}^{n} (x_i - \bar{x})^2 \sum_{i=1}^{n} (y_i - \bar{y})^2}} \]  

(3)

where \( r_{xy} \) is correlation coefficient, \( x \) and \( y \) being correlated variables, i.e., in this case \( x \) is SST whereas \( y \) is rainfall.

**Analysis of variations in rainfall**

Coefficient of variation is a widely applied method of variability analysis of rainfall (Beyene, 2016). Coefficient of variation \( (CV) \) provides a measure of year-to-year variation in the data series (Admasu, 2004). According to Cherkos (2001) and Hare (1983), \( CV \) is used to classify the degree of variability of rainfall events as less \( (CV < 20) \), moderate \( (20 < CV < 30) \), high \( (CV > 30) \), and very high \( (CV > 40\%) \) and \( CV > 70\% \) indicates extremely high inter-annual variability of rainfall. Similarly, in this study, coefficient of variation \( (CV) \) (standard deviation divided by the mean) was used in analyzing the variations in rainfall. Scientifically, it is computed using the following formula:

\[ CV = \left( \frac{s}{\bar{x}} \right) 100 \]  

(4)

where \( CV \) is coefficient of variation; \( s \) is the standard deviation and \( \bar{x} \) mean for annual and seasonal rainfall totals and temperature of 33 years from 1984 to 2016 inclusive.

**Result and discussion**

**Temporal fluctuations of total seasonal rainfall and mean seasonal sea surface temperature (SST)**

The long-term (from 1984 to 2016) total Kiremt rainfall reached highest and lowest values of 801.22 mm and 182.7 mm in 1994 and 1984, respectively, whereas the long-term mean value of the SST for the Kiremt season has highest and lowest values of 28.92 °C and 25.59 °C in 2015 and 1988, respectively, over the study period. Long-term total Belg rainfall would have experienced the highest value of 519.72 mm in 1987 and the lowest value of 37.10 mm in 2008. Moreover, in the analysis of mean Belg SST, the highest value of 28.9 °C and the lowest value of 26.23 °C were observed in 1992 and 2008, respectively, across the study area. Change curves of total Kiremt rainfall and mean Kiremt SST were fluctuating in an opposite direction from 1984 to 2015. However, from 2015 to 2016, the variation is slightly in the same direction (Figure 3). On the other hand, the variation of total Belg rainfall and mean Belg SST was in the same direction from 1985
to 1990, from 1997 to 2001, and from 2005 to 2011, while from 1990 to 1992 and from 1995 to 1996 the observed variation was in opposite direction (Figure 4). From this, it was observed that the variations of total Belg rainfall and mean Belg SST were almost in the same direction during the last 33 years across the study area. Throughout the study period, the highest and the lowest values of total Bega rainfall were 197.32 mm in 2014 and 8.18 mm in 1994, respectively, while the maximum and minimum mean Bega SST recorded were 28.81 °C in 2015 and 25.13 °C in 1988, respectively (Figure 5). From the figure, it was pointed out that the direction of variations of both total Bega rainfall and mean Bega SST was the same in most years of the study period undertaken. Likewise, the highest and the lowest values of long-term total annual rainfall were 1098.19 mm in 1998 and 359.77 mm in 1984, respectively. The highest value of mean annual SST was 28.62 °C in 2015, while the lowest value was 25.96 °C in 1999 (Figs. 6 and 7).

**Spatial distribution of mean total seasonal and annual rainfall**

Results of the analysis showed that the values of mean total rainfall were 473.26 mm in Kiremt season for the last 33 years. In Kiremt season, the amount of mean total rainfall revealed a spatial variation with values ranging from the lowest to the highest across the study area. The 33 years mean total rainfall was varied from 123.46 to 993.71 mm across the study area in Kiremt season (Figure 8). Highest rainfall value was found in
the northern and southeastern part of the study area, specifically in Lalibela, Dessie, and Kombolcha.

Similarly, the 33 years values of mean total rainfall were 48.48 mm in Bega season of the study area. Mean total Bega rainfall varied from 0.678 to 141.1 mm where the highest value was observed in southeastern part and the lowest one in southern and southwestern part of the study area (Figure 9). The average total Belg rainfall between 1984 and 2016 was 230.91 mm. According to the spatial distribution for the observation time in the study area, the highest values of mean total Belg rainfall were 623.58 mm, whereas the lowest values of mean total Belg rainfall were 12.49 mm. In Belg season, the highest amount of rainfall was revealed in southeastern part of the study area, while southwestern and western region received less amount of rainfall throughout the observation time (Figure 10). From this, it is possible to note that Belg rainfall showed high deviation across the study area.

The mean total annual rainfall of the study area varies temporally and spatially. From the analysis of this study, the amount of mean total annual rainfall was 753.63 mm over 33 years of the study area. With regard to spatial distribution, some parts of the study area were characterized by high amount of annual rainfall, while the remaining regions of the study area were experienced by low amount of rainfall for the last 33 years. It was observed that the highest value of mean total annual rainfall for the observation period of the study area was 1715.95 mm, whereas the lowest amount of mean total annual rainfall was 140.91 mm. From the study area, the highest rainfall was found in southeastern region and some part of northern area (Figure 10). Generally, the result showed that the mean total annual rainfall distribution varies both in space and in time.

Form this analysis, it is possible to conclude the spatial and temporal variation of rainfall be the cause to the failure of crop production in the study area, Wello.

**Temporal and spatial variability of mean total Kiremt/summer season rainfall (main rainfall season from June to September)**

The amount of mean total (both seasonal and annual) rainfall of the study area were varied spatially and temporally over the last 33 years. This climate variability was the main cause for crop failure and water scarcity in the region due to late onset of rainfall, short dry spells, and multi-annual droughts. In this study, rainfall data of the study area were analyzed for the magnitude of temporal and spatial variation using percentage of coefficient of variation (CV).

*Kiremt* rain has great significance over life of Ethiopian farmers. Since the economic activity is based on *Kiremt* rain, the variations occurred in each moment which later lead to rainfall variability can affect the maturity and development of crop.

The results of the temporal variability analysis of *Kiremt* rainfall across the study area are presented in Figure 11. Coefficients of variation (CV) which corresponds to the ratio of the standard deviation to the mean total *Kiremt* rainfall indicated that the variation of *Kiremt* rainfall was ranged from
22.8 to 62% across the study area over the last 33 years. The highest value of $CV$ was observed in southern and eastern regions, whereas the lowest value of $CV$ was found in the northern and southeastern regions of the study area. The complex spatial pattern illustrated the spatial heterogeneity of rainfall and indicated that topography factor may be responsible of this variability.

**Temporal and spatial variability of mean total Belg season rainfall (short rainy season in February to May)**

In Ethiopia, there are seasonal rainfall patterns that vary in number, intensity, duration, and timing, depending on location. The **Belg** season is particularly important for the production of fast-growing crops. According to NMSA (2001), the **Belg** season lasts February through May, which is a short rainy season.

In this study, the result of the analysis across the observation (1984–2016) demonstrated that the variation of mean total **Belg** rainfall ranged from 42.45 to 87.69% across the study area (Figure 12). The variation of mean total **Belg** was very high in most regions and extremely very high in some southern regions. From this, it is possible to note that the variation of **Belg** season rainfall was very high almost all parts of the study area during the last 33 years. Supporting this idea, Woldamlak and Conway (2007) arrived at a similar conclusion that **Belg** rainfall was more variable than **Kiremt** rainfall in their study that analyzed rainfall data from 12 stations in drought-prone areas of Amhara Region, Ethiopia.
Fig. 9 Spatial distribution of mean total Bega rainfall of the study area from 1984 to 2016

Fig. 10 Spatial distribution of mean total Belg rainfall of the study area from 1984 to 2016
Fig. 11 Spatial distribution of mean total rainfall of the study area from 1984 to 2016

Fig. 12 Temporal and spatial variability (CV) of mean total Kiremt rainfall (RF) of the study area from 1984 to 2016
Temporal and spatial variability of mean total annual rainfall

The annual mean total rainfall of the study area varied temporally and spatially. The results of spatio-temporal variability analysis revealed the lowest and the highest variation (CV), which were 23.13% (moderate) in southeastern region and 57.86% (very high) in southern part, respectively, across the study area for the last 33 years (Figure 13). Generally, the result showed that the mean total annual rainfall distribution across all the observation period varied in both space and time (Fig. 14).

The association of sea surface temperature (SST) with rainfall both seasonally and annually

The correlation between Kiremt rainfall total and mean SST was negative ($r = -0.457$) and statistically significant at alpha level 0.05. Belg rainfall total, on the other hand, portrayed the opposite, means Belg rainfall total has positive correlation ($r = 0.385$) and statically significant at alpha 0.05 level. This implies that SST causes the declined of the amount of rainfall in Kiremt season and the opposite was true for Belg rainfall across the study area over the last 33 years. This is supported by Bekele (1993) and Woldegiorgis (1997) who both identified similar inter-seasonal correspondence. Another study made by Sintayehu et al. (2017) reported that during Belg season rainfall anomaly and related Nino regions were positively correlated, while during Kiremt season rainfall anomaly and SST anomaly were negatively correlated. Similarly, the correlation between Bega rainfall total and mean Bega SST as well as annual rainfall total with mean annual SST were positive in the study area.

The amount of rainfall in La Niña years was higher than El Niño years. Similar result was obtained in this study, and the amount of annual rainfall total was higher in La Niña years (886.13 mm in 1988 and 704.84 mm in 2011) than El Niño years (384.66 mm in 2002 and 583.24 in 2015). Kiremt rainfall total (632.31 mm in 1988 and 464.84 in 2011) during La Niña was also higher than Kiremt rainfall total (199.18 mm in 2002 and 194.12 mm in 2015) in El Niño years. Similarly, the amount of Belg rainfall total was higher in La Niña years (227.04 mm in 1988 and 216.53 mm in 2011) than El Niño years (129.26 mm in 2002 and 195.28 mm in 2015). On the contrary, Bega rainfall total was less in La Niña years (26.78 mm in 1988 and 19.46 mm in 2011) than El Niño years (56.22 mm in 2002 and 193.83 mm in 2015). As to the finding of this research, similar results were reported in the study made by Getahun and Shefne, 2015 in Gojjam. In Ethiopia, El Niño reduces the amount of rainfall in summer. This study also showed the same phenomenon for Wello (Table 3).

Relationship between rainfall and cereal production

To determine the relationship and effect of rainfall (monthly, seasonal, and annual rainfall totals) on crop production in the study area, linear regression analysis was employed. The result of correlation coefficient ($r$) and coefficient of determination ($R^2$) from linear regression between rainfall totals (monthly, Kiremt, and annual) and cereal Meher production on the study area are given in Table 4.
At the monthly time scale, correlations between rainfalls during May to September and cereal productions were all positive in this study. May to September covers the period from preparation of fields and sowing to maturity stage of crops. The correlation between Meher teff production (qt/ha) with May, June, July, September, and August rainfalls were $r = 0.141$, $r = 0.244$, $r = 0.336$, $r = 0.646$ significant at alpha 0.05 level, and $r = 0.346$, respectively, and it has been observed that as there was moderately strong relationship between teff production and August rainfall. The coefficient of determination ($R^2 = 0.417$) from linear regression between August rainfall and teff production indicated that 41.7% of the variation in teff production in the study area was explained by the variations in August rainfall. This finding is in line with a study conducted by Alemayehu and Bewket (2016) focused on local climate variability and crop production in the Central Highlands of Ethiopia and reported that August rainfall shows statistically significant strong positive correlation with production of teff. The correlation between Meher barley production (qt/ha) with May, June, July, September, and August rainfalls are $r = 0.304$ significant at alpha 0.05 level, $r = 0.267$, $r = 0.135$, $r = 0.059$, and $r = 0.152$, respectively. The association between Meher wheat production (qt/ha) with May, June, July, September, and August rainfalls are $r = 0.695$ significant at alpha 0.05 level, $r = 0.466$, $r = 0.706$ significant at alpha 0.01 level, $r = 0.527$ significant at alpha 0.1 level, and $r = 0.656$ significant at alpha 0.05 level, respectively. This implied that the correlation of wheat production with monthly rainfall was moderately strong and significant except June rainfall. The coefficient of determination ($R^2 = 0.498$) from linear regression between July rainfall and wheat production showed that 49.8% of the variation in wheat production in the study area was explained by the variations in July rainfall that indicated as July rainfall increases, wheat production increases as compare to the other monthly rainfalls.

The correlation between Meher maize production (qt/ha) with May, June, July, September, and August rainfalls were $r = 0.568$ significant at alpha 0.1 level, $r = 0.619$ significant at alpha 0.05 level, $r = 0.614$ significant at alpha 0.05 level, $r = 0.599$ significant at alpha 0.05 level, and $r = 0.254$, respectively. Here, maize production is correlated moderately strong with June and July rainfall and is associated moderately with May and August rainfall, but weakly related with September rainfall. This explains how much rainfall variation explains the variation of maize production in the study area.

### Table 3

| Total rainfall vs. mean SST | $r$  | $p$ value |
|-----------------------------|------|-----------|
| Kiremt                      | −0.457 | 0.008 |
| Belg                        | 0.385 | 0.027 |
| Bega                        | 0.349 | 0.047 |
| Annual                      | 0.034 | 0.973 |

Example, the linear regression analysis between Meher maize production (qt/ha) and June rainfall indicates that coefficient of determination ($R^2 = 0.384$), implying that the impact of June rainfall accounts for 38.4% of maize yield changes, while 61.6% of variation in maize yield was explained by other
factors, such as the use of fertilizers, better crop management practices, etc. The correlation of Meher sorghum production (qt/ha) with May, June, July, September, and August rainfalls are $r = 0.546$ significant at alpha 0.1 level, $r = 0.593$ significant at alpha 0.05, $r = 0.527$ significant at alpha 0.1 level, $r = 0.630$ significant at alpha 0.05 level, and $r = 0.494$ significant at alpha 0.1, respectively. August rainfall was the most important determinant factor for the variation in sorghum production. Similar to the finding to this study, previous studies reported positive correlation between rainfall and crop production in Nigeria, Ethiopia, Uganda, and Tanzania (Beweket, 2009; Rowhani et al., 2011; Adangbe and Ujoh, 2013; Akintsye et al., 2013; Mwaura and Okoboi, 2014; Yamusa et al., 2015).

The correlation coefficients computed between Meher crop yield (teff, barely, wheat, maize, and sorghum) and Kiremt rainfall totals in this study area showed from low to moderately strong and positive relationship. The correlation of Kiremt rainfall totals with teff, barely, wheat, maize, and sorghum were $r = 0.341$, $r = 0.343$, $r = 0.659$, $r = 0.736$, and $r = 0.689$, respectively. Here, it has been observed that total Kiremt rainfall has statistically significant correlation with the production of barely, wheat, maize, and sorghum. The linear regression analysis indicates that coefficient of determination ($R^2$) describes the proportion of the total variance in the observed crop data explained by Kiremt rainfall totals. For example, in this study, the regression analysis between Meher maize production (qt/ha) and Kiremt rainfall indicates that coefficient of determination ($R^2 = 0.541$), implying that the impact of Kiremt rainfall totals account for 54.1% of maize yield changes, while 45.9% of variation in maize yield was explained by other factors. Annual rainfall totals have statically significant at significant level alpha 0.1, positive and moderately strong correlation with Meher maize and sorghum yields (qt/ha), but week and statically non-significant correlation with teff, barley, and wheat production.

Even though the correlations between annual rainfall totals and crop productions taken understudy were positive, most are not significant in statistical terms. This can be due to short length of the production data used and consideration of rainfall isolating from all other agronomic factors such as growing period, radiation, temperature, pests, diseases, etc. Generally, rainfall has very important contribution to get the required amount of crop yields.

**Conclusion**

Ethiopia is susceptible to climate variability and change. The effects of climate change may exacerbate existing social and economic encounters across the country, mainly where people are reliant on resources that are sensitive to climate variability and Kiremt rain-fed agriculture. In this study, an attempt has been made to analyze climate variability and its impact on crop production by applying GIS and statistical analysis in the study area, where agricultural activities have been highly influenced by climate variability. In light of the evidences that were obtained from the study, the following conclusions could be drawn.

With regard to spatial and temporal distribution, the finding of this study revealed that the amount of seasonal and annual rainfall varies temporally and spatially across the study area during the last 33 years. It was observed that the southeastern and northern regions (Lalibela, Dessie, Kombolcha) received the highest amount of mean total Kiremt rainfall (993.71 mm) and mean total annual rainfall (1715.95 mm). Furthermore, rainfall data of the study area was analyzed for the magnitude of temporal and spatial variations using percentage of coefficient of variations (CV). CV of mean total Kiremt and annual rainfall were ranging from 24.8 to 62% and from 23.13 to 57.86%, respectively. The variation was high in southern and southeastern part of the study area. Generally, the variations of rainfall were the main cause for crop failure and water scarcity in the region, particularly, due to late onset of rainfall, short dry spells, and multi-annual droughts.
The associations between total Kiremt and Belg rainfall with mean sea surface temperature were negative \( (r = -0.457) \) and positive \( (r = 0.385) \), respectively and statically significant at alpha 0.05 level. This implies that sea surface temperature caused the declined of the amount of rainfall in Kiremt season and the opposite was true for Belg rainfall across the study area over the last 33 years. The results of regression analysis of crops with total Kiremt rainfall revealed that Meher crop yields (qt/ha) (teff, barely, wheat, maize, and sorghum) have coefficient of determination \( (R^2) 0.116, 0.118, 0.434, 0.542, \) and 0.475, respectively, indicating that 11.6%, 11.8%, 43.4%, 54.2%, and 47.5% of variations in teff, barely, wheat, maize, and sorghum production in this study area could be, respectively, explained by the variations in total Kiremt rainfall, while the remaining percentage variation in each yield was explained by other factors, such as better seeds, better crop management practices, introduction of new agro-technology, and other unexplained. Therefore, it is clear from the analysis that climate change is clearly happening in Ethiopia as well as in Wello and appropriate adaptation strategies should be properly designed and implemented.

Generally, the analysis of this study revealed that rainfall variability is one of the major determinant factors for variation of major crop yields in the study area, and this information might be used as an input for decision-makers take appropriate adaptive measures in various agricultural and water resource sectors. However, more comprehensive study by including other climatic elements like wind speed, solar radiation, and soil moisture data are required in the study area.

Policy implications

Having good knowledge of rainfall spatial distribution, variability, relationship with sea surface temperature, and its impact on crop yields plays an important role in management of water resource and agricultural productivity, to take climate risk management approach for adapting to the ongoing climate change, as well as for the planning of farming practice and drought assessment.

Hence, the finding of this study should be used to design a better supporting mechanism in different development activities of North and South Wello zones, such as, expanding irrigation and water management practices, strengthening awareness of farmers and early warning responses, shift to early maturing and drought-resistant crops, diversifying livelihood opportunities, promoting perennial trees like fruits in the highlands and fast maturing cash crops in the lowlands, intensive use of inputs, and better land management practices are some of the strategies.

In general, the finding of this study will have great contribution to the global community to understand the spatial and temporal variability of rainfall, its impact on crop yields, and the relationship of rainfall with sea surface temperature in order to design different intervention strategies.

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Data availability For this research, CFSR rainfall was obtained by bounding box of latitude 8.6896°S, longitude 36.0956°W, latitude 13.3148°N, and longitude 40.2045°E (the Texas A&M University spatial sciences website, globalweather.tamu.edu).

Declarations

Ethics approval I hereby declare that this study is my original work and has not been published in any other journals, and all sources of material used for this study have been duly acknowledged. I would like to confirm that I have consented to publish this article at this journal/Journal of Climate Change.

Conflict of interest I declare that no conflict of interest. The funder has not been published in any other journals, and all sources of material used for this study have been duly acknowledged. I would like to confirm that I have consented to publish this article at this journal/Journal of Climate Change.

References

Adamgbe E, Ujoh F (2013) Effect of variability in rainfall characteristics on maize yield in Gboko, Nigeria. J Environ Prot 4:881–887
Admassu S (2004) Rainfall variation and its effect on crop production in Ethiopia. MSc Thesis, Department of Civil Engineering, Addis Ababa University
Afifi T, Liwenga E, Kwezi L (2014) Rainfall-induced crop failure, food insecurity and outmigration in Same-Kilimanjaro, Tanzania. Clim Dev 6(1):53–60
Afisar S, Nasir A, Bulbul J (2013) Comparative study of temperature and rainfall fluctuation in Hunza-Nagar District. J Basic Appl Sci 9:151–156. Retrieved from (https://creativecommons.org/licenses/by-nc/3.0/). Agro-ecology resources of Ethiopia, Addis Ababa, Ethiopia, 1(1):0–137
Akinseye F, Ajayi V, Oladitan T (2013) Assessing the impacts of climate variability on crop yield over Sudano- Sahelian zone in Nigeria. Access Int J Agric Sci 1(7):91–98
Alhamshry A, Fenta AA, Yasuda H, Kimura R, Shimizu K (2020) Seasonal rainfall variability in Ethiopia and its long-term link to global sea surface temperatures. Water (Switzerland) 12(1). https://doi.org/10.3390/w12010055
Babu A (1999) (NMSA). Lecture notes: the impact of Pacific sea surface temperature on the Ethiopian rainfall. 1st DMC Nairobi capacity building workshop, 11 January to 15 February 1999. Unpublished lecture notes. (Coated by T. W. Giorgis, The Case of Ethiopia, July 2000)
Barrett CB (1994) The development of the Nile hydro meteorological forecast system. Water Resour Bull 29:933–938
Woldamlak B, Conway D (2007) A note on the temporal and spatial variability of rainfall in the drought-prone Amhara region of Ethiopia. Int J Climatol 27:1467–1477

Wu R, Kirtman BP, Pegion K (2008) Local rainfall-SST relationship on subseasonal time scales in satellite observations and CFS. Geophys Res Lett 35. https://doi.org/10.1029/2008GL035883

Yamusa A, Abubaker I, Falaki A (2015) Rainfall variability and crop production in north western semi-arid zone of Nigeria. Journal of Soil Science and Environmental Management 6(5):125–131

Yitea S (2012) Spatial-temporal analyses of climate elements, vegetation characteristics and sea surface temperature anomaly. MSc Thesis in Geospatial Techniques, University of Erasmus Mundus, the Netherlands

Zaroug M (2010) The connections of Pacific SST and drought over East Africa. DEWFORA meeting at ECMWF, improved Drought Early Warning and FORecasting to strengthen preparedness and adaptation to droughts in Africa (DEWFORA), United Kingdom, 4–5 October

Zhang Q, H Kornich, Holmgren K (2012) How well do reanalyses represent the Southern African precipitation? Clim Dyn 40:951–962. https://doi.org/10.1007/s00382-012-1423-z