Precipitation Variability and its Teleconnection with the Global SST and ENSO Indices in the Food Insecure Rural Areas of Tigray

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Abstract

The impact of precipitation variability on food production is very significant. For food insecure rural areas, understanding the nature of precipitation variability and its teleconnection has paramount importance in guiding regional and local level decisions. In this study, we analyzed the monthly, seasonal and annual precipitation variability and the strength of its teleconnection with the global sea-surface temperature (SST) and El Niño Southern Oscillation (ENSO) indices in the food insecure rural areas of Tigray region, Ethiopia. The precipitation, SST, and ENSO indices data for the study were used from 1979 to 2019. A Summary of descriptive statistics and Mann Kendall test methods were applied to detect existence of trends; and Sen's Slope and coefficient of variation are used to analyze the magnitude of the trend, and degree of variation in the trend of precipitation. Further, Pearson's correlation is used to determine the effect of ENSO, and SST variations on the precipitation using the Canonical Correlation Analysis (CCA). The results revealed that the precipitation over the study areas is characterized by a distinctive bi-modal pattern with limited rains in March – May preceding the main rainy season June – September. The limited amount of precipitation, exacerbated by higher degree of variability, makes the food production in the study areas more uncertain. Besides, there was a very significant decline in the trend of March – May average precipitation and a significant decline in the trend of the annual average precipitation of Hintalo area. The SSTs of the central and eastern equatorial Pacific Ocean, and northeast and northwest equatorial Atlantic Ocean was strongly correlated with April's average precipitation of the study areas. Further, the SST of south, west and southwest of equatorial Indian Ocean, and west equatorial Pacific Ocean were associated with July – September average precipitation with greater variation in strength among of the study areas. Moreover, July's average precipitation of all the study areas, April's average precipitation of Atsbi and Eirop, and May's precipitation of Hintalo are found significantly associated with the ENSO indices of JFM, FMA, MJJ and MAM. Therefore, the task of achieving food security in the study areas should incorporate the design of informed food production strategies that can adapt the limited and variable precipitation based on these SST and ENSO indices.

Keywords: climate change, food security, sea-surface temperature, El Niño

Introduction

Climate change, the catchy phrase, is the major threat to food security in rural areas. Because of the limited capacities to cope up with the varying climate, food insecurity is higher in rural areas of developing countries, where much of their population depends on rain to produce food. World Bank (2016) reported that rural farmers are more than four times as likely to be food insecure as compared to urban dwellers engaged in non-agricultural sectors. According to the findings of a research conducted across 105 countries by Alkire *et al*. (2014), 86 percent of food insecure people of Sub-Saharan Africa and South Asia live in rural areas.

Although many factors are associated with food insecurity in rural areas, food shortage, the main feature of food insecurity, is often associated with precipitation shortage and variability. A number of scholars like Darwin (2001), Schmidhuber and Tubiello (2007), Wheeler and Braun (2013), agree on the significant impact of precipitation variability on food production. Kinda & Badolo (2019) showed that precipitation variability has reduced food availability per capita and increased fluctuation in food production for 71 developing countries from 1960 to 2016. According to Von Braun (1991), a 10 percent decline in the average amount of precipitation leads to a 4.4 percent reduction in the food production.

Ethiopia is predominantly an agrarian nation, in which more than 80 percent of the population relies on agriculture. More importantly, nearly 90 percent of the smallholder farmers mainly depend on rain-fed agriculture (Alhamshry *et al*., 2020). For this reason, Ethiopia listed as the most vulnerable to adverse impacts of climate variability (World Bank, 2010). Yet, not all parts of the country are equally vulnerable to the impacts of climate variability. Subsistence farmers were relatively the most susceptible to climate variability in Ethiopia (Asfaw *et al*., 2018). Subsequently, the problem of food insecurity in Ethiopia is more pronounced in rural areas (World Finance, 2017). Further, an overdependence on the rain-fed agriculture was one of the reasons for the pervasiveness of food insecurity in rural Ethiopia (Mekonnen & Gerber, 2017).

In Ethiopia, the intensity and variability of precipitation have been important determinants of food security in rural areas (Demeke, 2011; Alemayehu & Bewket, 2016; and Agidew & Singh, 2018). During the period of 1983-1985, Ethiopia's Tigray region experienced the severest food insecurity induced by drought which caused an estimated one million people deaths (Reid, 2018). In the period of 2015-2016, an El Niño induced drought took place mainly in the lowlands

of the country (Singh *et al*., 2016). During that time, a quarter of Ethiopian population was food insecure and more than 18 million people were requesting for urgent food aid (Mohamed, 2017).

Tigray is one of the regions in Ethiopia, which, over the past many decades have been affected by recurrent droughts (Endalew *et al*., 2015). In the region, the average precipitation is very short and variable as compared to the southern and western parts of Ethiopia (Seleshi & Demaree, 1995; Woldehanna, 2000; and Weldearegay & Tedla, 2018). The average annual precipitation of Tigray for the last 20 years was 725mm (Weldearegay & Tedla, 2018). According to Demeke *et al*. (2011) and Weldearegay & Tedla (2018), precipitation variability was the major cause of food shortage in Tigray region. Having this uncertain and lesser precipitation, the rural farmers in Tigray still depend on the unreliable precipitation to produce food.

Although precipitation variability has many forms, the intensity and timing in the precipitation pattern is the main form of variability. According to Torres *et al*. (2019), variations in timing and intensity of precipitation are higher in an intra-year than inter-yearly. Intra-year variability matters most as many rural farmers keep months and seasons to do the farming activities.

Precipitation variability is highly determined by global sea-surface temperature (SST) and El Niño Southern Oscillation (ENSO). The SST is among the major drivers of precipitation variability (Dittus *et al*., 2018), particularly for the Ethiopian precipitation (Alhamshry *et al*., 2020). Besides, the ENSO is the other most important determinant of precipitation variability, particularly in the precipitation pattern of Ethiopia (Kasie *et al*., 2019 & Tefera *et al*., 2020). These two factors highly determine the intra-year and inter-year precipitation variability.

However, different areas have variant sensitivities to the SST and ENSO indices; and the impacts of those indices greatly vary from place to place. Hence, studies of precipitation variability and its associated climate factors have to be conducted at the lowest possible geographical spaces. Furthermore, how significant is the influence of SST and ENSO in the precipitation variability of the food insecure rural areas of Tigray region has not been well researched before.

Therefore, this study will investigate the precipitation time-series trend on monthly, seasonal and annual scales, its degree of variability, and detect the significance of the global SST and ENSO indices impact on the precipitation pattern of the food insecure rural areas of Tigray region, Ethiopia. This would be crucial for guiding local level food production related decisions and indicate feasible adaptation strategies to reduce the risk in food production.

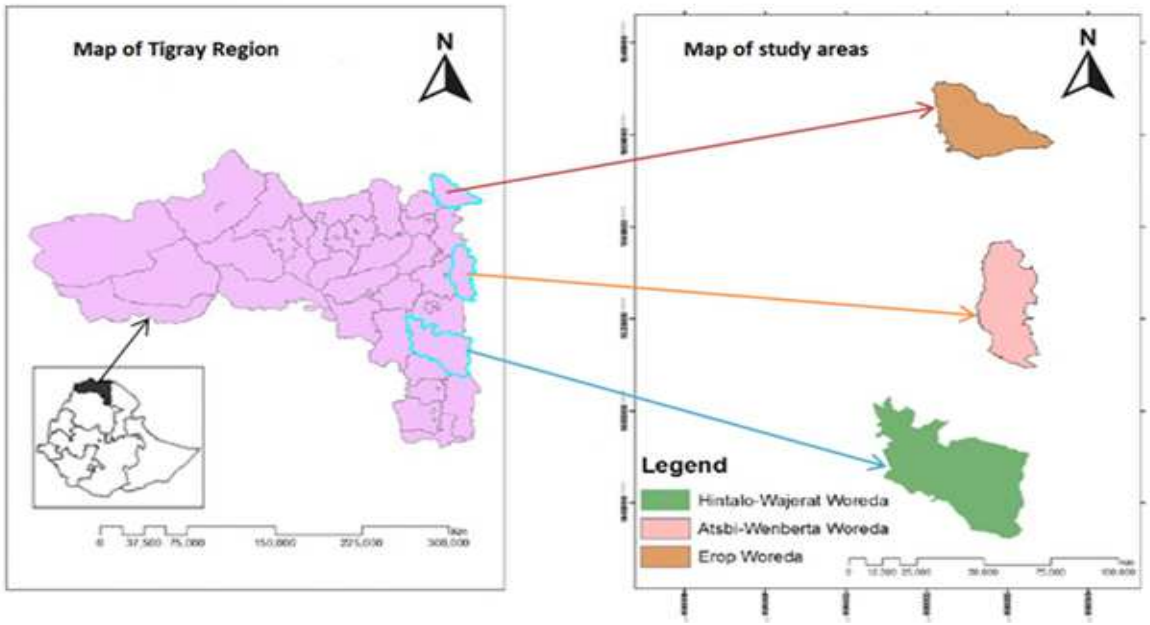
Methodology

The study has constituted top three food insecure rural districts found in Tigray region. All these three districts were purposefully selected based on the recent data from the regional office of food security. Accordingly, rural areas of Atsbi Wenberta, Eirop, and Hintalo Wajerat districts were the three most food insecure rural districts of Tigray region.

Table1: Geographical location of study areas

Name of study areas	Elevation (m)	Latitude (North)		Longitude (East)	
Atsbi Wenberta	2511	13.8465	13.9132	39.6763	39.7903
Eirop	1931	14.4291	14.5528	39.3695	39.5974
Hintalo Wajerat	2107	13.2677	13.3572	39.5013	39.6908

Figure 1: Map of the Study areas



This study is based on a secondary data on which precipitation data of the study areas for the period of 1979 - 2019 were gathered from the Ethiopian National Meteorological Agency and CFSR. The global SST and ENSO data for the specified period were gathered from IRI/LDEO Climate Data Library and from the US National Oceanic and Atmospheric Administration (NOAA) Climate Prediction Center, respectively.

Mann-Kendall test, Sen's Slope and coefficient of variation are used to analyze the significance, magnitude, and degree of variation in the trend in precipitation pattern of the study areas. Further, Canonical Correlation Analysis tool (CCA) is used to analyze the

correlation between the areal precipitation and sea-surface temperature, and Pearson correlation is used to test the relationship with the SST and ENSO indices.

The Mann-Kendall test is calculated as equation 1:

$$S = \sum_{i=1}^{n-1} . \sum_{j=i+1}^{n} \operatorname{sgn}(X_j - X_i) \quad (1)$$

Where S is the Mann-Kendal's test statistics, n is the number of data points, X_j and X_i are the data values in the time series j and i ($j > i$) respectively. The $\operatorname{sgn}(X_j - X_i)$ is the sign function as indicated in equation (2):

$$\operatorname{sgn}(X_j - X_i) = \begin{cases} +1 \text{ if } (X_j - X_i) > 0 \\ 0 \text{ if } (X_j - X_i) = 0 \\ -1 \text{ if } (X_j - X_i) < 0 \end{cases} \quad (2)$$

The variance is calculated as equation (3):

$$Var\ (s) = \frac{n(n-1)(2n+5) - \sum_{i=1}^{m} t_i(t_i-1)(2t_i+5)}{18} \quad (3)$$

Where n is the number of data points, m is the number of tied groups (a set of sample data that have the same value), the summation sign (Σ) indicates the summation over all tied groups, and t_i is the number of data point for the ith tie. If there are no tied groups, this summation process can be ignored. In the case where the sample size $n > 10$, Z_{MK} approximates the standard normal distribution with the mean (S) = 0 and computed using equation (4):

$$Z_{MK} = \begin{cases} \frac{S-1}{\sqrt{Var\ (S)}} \text{ if } (S) > 0 \\ 0 \quad \text{ if } (S) = 0 \\ \frac{S+1}{\sqrt{Var\ (S)}} \text{ if } (S) < 0 \end{cases} \quad (4)$$

The presence of a statistically significant trend is evaluated using the Z_{MK}value. Positive values of Z_{MK} indicate increasing trends, while negative Z_{MK} values show decreasing trends. Testing trends are performed at the specific α (0.05) significance level. When $|Z_{MK}| > Z_{1-\alpha/2}$, the null hypothesis is rejected, indicating that a significant trend exists in the time series. $Z_{1-\alpha/2}$ is the critical value of Z_{MK} is obtained from the standard normal distribution table which is 1.96.

The Mann–Kendall test only indicates the direction; hence, the magnitude of the trend is usually determined by Sen's test which is defined by calculating the slope. The slope (change per unit

time) was estimated based on the procedure in equation (5) and (6).

$$Q_i = \frac{(X_i - X_j)}{i-j} \qquad (5)$$

Where X_i and X_j are considered as data values at time *i* and *j* (*i* >*j*) correspondingly and Q is the Slope. The Sen's estimator is computed as $Q_{med} = Q_{\frac{N+1}{2}}$ if N appears odd, and it is considered as $Q_{med} = \frac{1}{2}(Q_{\frac{N}{2}} + Q_{\frac{N+2}{2}})$ if N appears even which is given as:

$$Q_{med} = \begin{cases} Q_{\frac{N+1}{2}} & if\ N\ is\ odd \\ \frac{1}{2}\left(Q_{\frac{N}{2}} + Q_{\frac{N+2}{2}}\right) & if\ N\ is\ even \end{cases} \qquad (6)$$

Q_{med} is computed by a two-sided test at 100 (1-α) % confidence interval and then a true slope can be obtained by the non-parametric test. Positive value of Q_{med} indicates an upward or increasing trend and a negative value of Q_{med} gives a downward or decreasing trend in the time series.

Coefficient of variation of the annual precipitation variation is calculated as equation 7:

$$CV = \frac{Sd}{\bar{X}} * 100 \qquad (7)$$

Where Sd is the standard deviation which is computed by square root of the variance, and $\bar{X}$ is the sample mean of the annual average precipitation.

In this study, we use Pearson's correlation coefficient with the significance assessed using the precipitation pattern of the study areas and the likelihood global SST and ENSO variations. The Pearson correlation coefficient in this study is defined as follows: Suppose that there are two variables *X* and *Y*, each having *n* values *X1, X2, … Xn*, and *Y1, Y2, … Yn*, respectively. Let the mean of *X* be $\bar{x}$ and the mean of Y be $\bar{y}$. Then, Pearson's *r* is given by

$$r = \frac{\sum (X_i - \bar{X})(Y_i - \bar{Y})}{\sqrt{\sum (X_i - \bar{X})^2 \sum (Y_i - \bar{Y})^2}}, \qquad (8)$$

where the summation proceeds across all possible values of and in this sample.

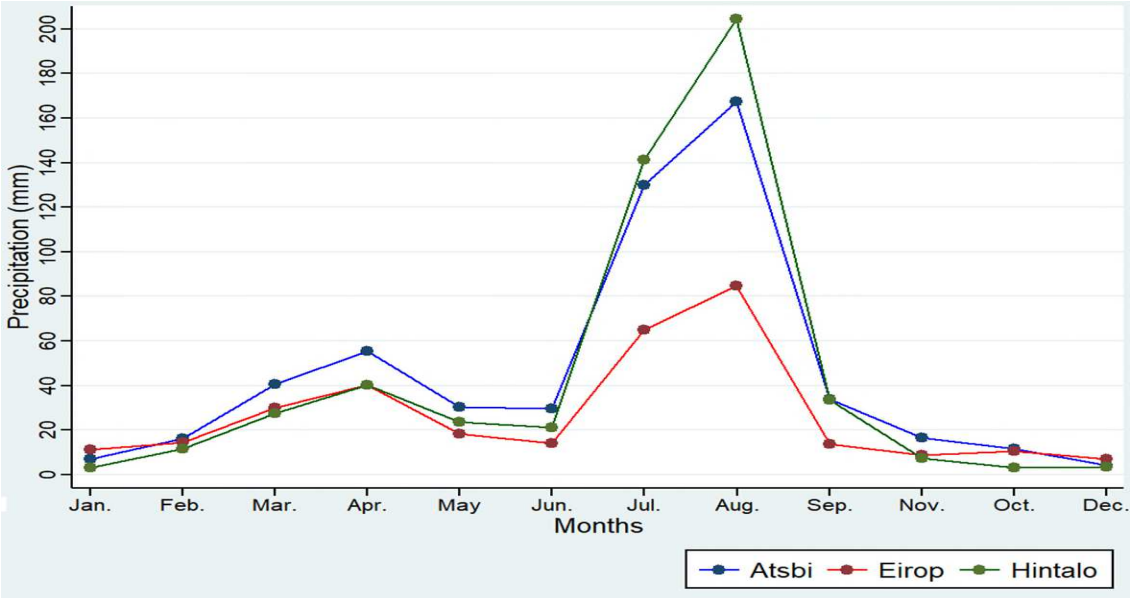
Results and Discussions

In Ethiopia, particularly in Tigray region, smallholder farming is the common agricultural practice where farmers usually depend on precipitation. For the reason that precipitation is a natural phenomenon that varies timely and spatially, understanding the nature of precipitation variability can minimize the possible risks on rural households. It can also significantly improve the food security status of the vulnerable rural community.

Food insecurity, in many parts of the world, is associated with shortage of rainfall (Afifi *et al*., 2014); and in Ethiopia, rainfall variability is among the primary drivers of food security (Lewis, 2017). In areas where rainfall is relatively low, efficient utilization of the precipitations of all the time matters most. Atsbi wenberta, Eirop, and Hintalo wajerat are the most food insecure rural areas of Tigray region. Table 1 shows that these areas can get precipitations in any month of the year. This implies for an enhanced utilization of the water precipitated in any time and place of these areas.

Regardless of the variation in the amount of precipitation, figure 2 shows that all the study areas have a bimodal nature of rainfall pattern with higher and lower amount of precipitation during the JJAS and MAM seasons, respectively. This corresponds with findings of Kahsay *et al.*, (2019) & Gebru (2020) who found a bimodal nature of rainfall pattern in Eastern Tigray and southern Tigray. In the study areas, August was found to be comparatively the rainiest month with maximum average amount of precipitations in the time span; and the precipitation during July has never been zero for the last 41 years. The monthly average amount of precipitation was relatively lower from October to February; and it was higher during June to September. Yet, the range between the maximum and minimum amount of monthly precipitations was extremely higher in the rainy months than the drier months.

Figure 2: Monthly average precipitation of the study areas (1979-2019)



The average annual precipitation of the study areas, i.e. *Atsbi*, *Eirop*, and *Hintalo* was found to be 542.5, 318, and 520.7mm, respectively. This is much lower than the national average and even from the regional average. According to Weldearegay & Tedla (2018), the average annual precipitation of Tigary region for the last 20 years was 725mm. Although crop production with these amounts of rainfall may be possible, it is not sufficient and reliable. In line with this, FAO (1986) suggests irrigation based crop production in areas where average annual precipitation is less than 1200mm. FAO (1986) also suggests that irrigation is a must in areas with less than 400mm of average annual precipitation. In the study areas, let alone the average annual precipitation, the maximum annual precipitation recorded in the last 41 years was less than 1200mm. More extremely, the maximum annual precipitation for Eirop district was only 643.9mm. In this condition, achieving food security would be difficult using the conventional farming system.

Table 2: Maximum, minimum and average precipitation during the period of 1979 – 2019

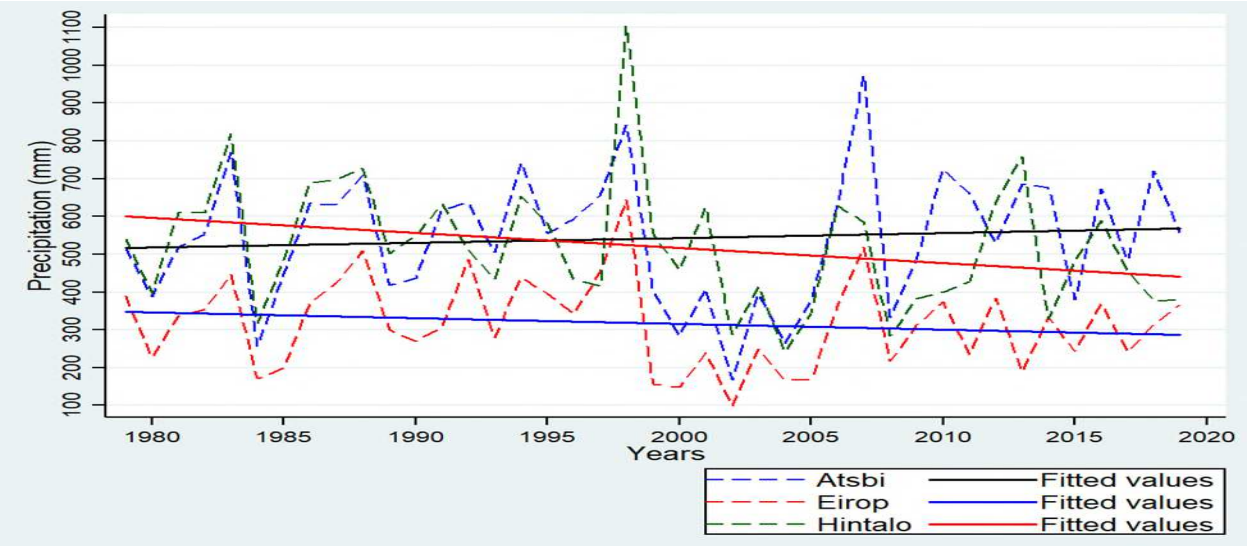
Time	Average precipitation (mm)			Maximum precipitation (mm)			Minimum precipitation (mm)		
	Atsbi	Eirop	Hintalo	Atsbi	Eirop	Hintalo	Atsbi	Eirop	Hintalo
January	7.1	11.3	3.1	38.5	66.4	30.6	0.0	0.0	0.0
February	16.3	14.6	11.7	88.3	78.5	81.3	0.0	0.0	0.0
March	40.5	29.9	27.6	184.0	153.9	202.0	0.0	0.0	0.0

April	55.4	40.2	40.3	141.8	116.0	173.9	0.0	0.0	0.0
May	30.2	18.5	23.7	115.3	84.1	145.8	0.0	0.0	0.0
June	29.5	14.0	21.2	158.2	116.5	131.2	0.0	0.0	0.0
July	129.9	64.9	141.1	333.9	180.0	346.6	14.0	6.8	19.4
August	167.4	84.6	204.4	366.0	318.5	674.6	55.0	0.0	53.3
September	33.9	13.7	33.7	155.5	58.0	260.4	0.0	0.0	0.0
October	16.6	8.7	7.3	206.0	126.9	50.1	0.0	0.0	0.0
November	11.5	10.6	3.3	67.0	88.4	30.9	0.0	0.0	0.0
December	4.3	6.9	3.5	50.4	51.8	44.6	0.0	0.0	0.0
MAM	126.1	88.6	91.5	327.6	238.0	392.4	11.1	0.0	0.0
JJAS	360.7	177.2	400.3	800.5	443.9	965.0	84.8	29.6	152.8
Annual	542.5	318.0	520.7	972.8	643.9	1103.5	166.7	99.4	241.2

When we see the variability in the annual precipitation depicted in Figure 3, there was a similar trend for the three study areas till 2008. Yet, it is observed that there was a steady increment in the average annual precipitation of Atsbi; whereas, there was a decrement for the other two sites. The decrement in the average annual precipitation of Hintalo was found to be statistically significant ($P<0.05$), as shown in table 3.

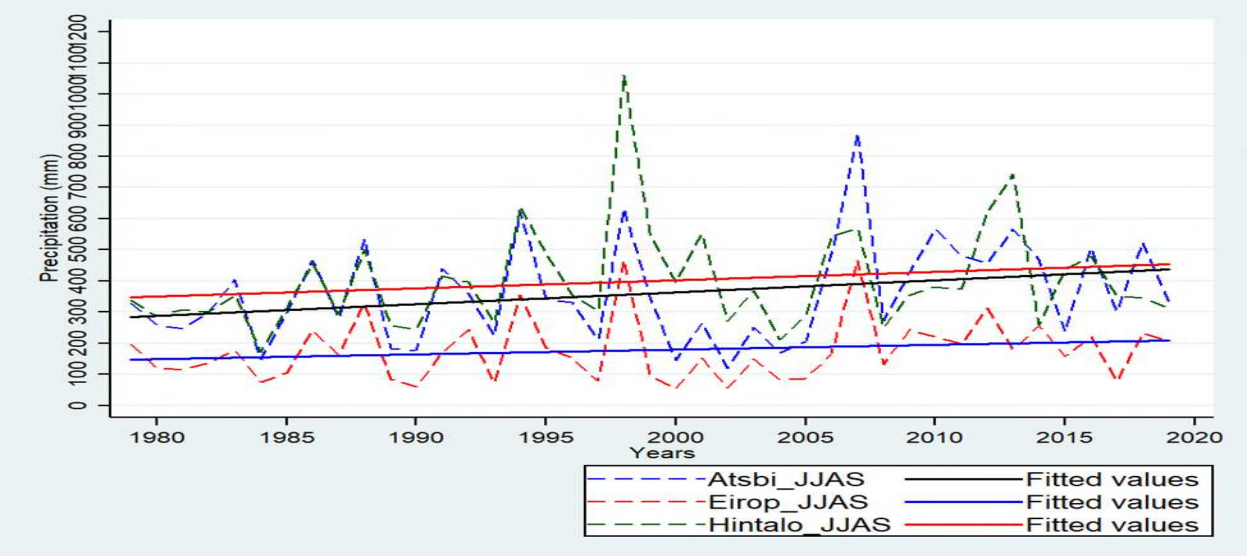
When we see the trend in the annual precipitation at larger scale, Onyutha *et al*. (2016) found that long-term trends in the annual precipitation of Sudan, Ethiopia and Egypt were mostly negative. On the other hand, the annual precipitation projected by Ongoma *et al*. (2018) & Cook *et al*. (2020) indicates a significant increase in annual precipitation over East Africa. This implies that the models that have been projecting the possible trends in precipitation, unless cascaded to the local level, would affect the decisions of relevant actors in handling food insecurity.

Figure 3: Trend in the annual total precipitation (1979-2019)



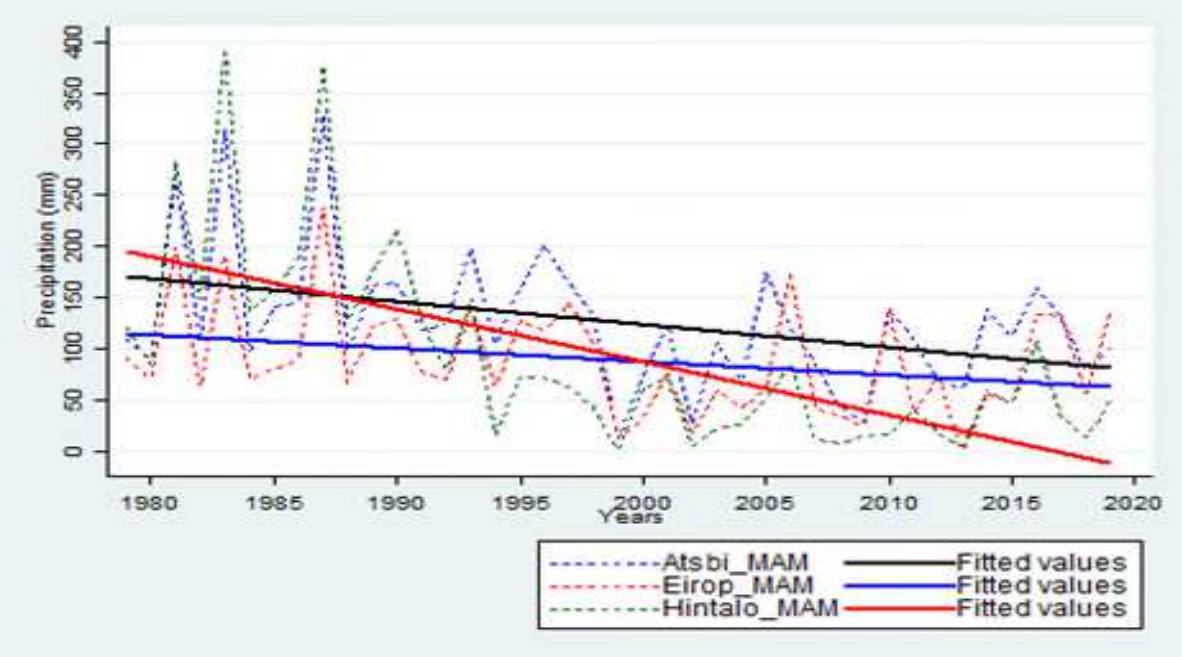
For the JJAS (June – September) season, all the study areas have experienced a statistically insignificant increase in the average precipitation, as shown in figure 4. This season is the most important in agricultural production of the study areas and Ethiopia in general. Although there is no a significant variability in this season, the coefficient of variability within the months of the season was very high (see table 3). Besides, variability in the onset and cessation time of precipitation in East Tigray during the JJAS season was higher in the last 15 years (Kahsay *et al.*, 2019). Thus, depending on the variable rain can affect food security status of the prone areas.

Figure 4: Trend in the June – September (JJAS) total precipitation



The MAM (March – May) season is the other important rainy season for all over the region next to JJAS season. During this season, unlike the JJAS, all the study areas have experienced a decrease in their average precipitation, as shown in figure 5. The decrement was again statistically very significant (P<0.01) for Hintalo district, as shown in table 3. This trend variability needs to be considered in any future agricultural or rain-water harvesting activities of the MAM season.

Figure 5: Trend in the March – May (MAM) total precipitation



When we see the variability in the average amount of monthly precipitation, the Mann-kendall test in table 3 illustrates the study areas showed statistically insignificant decreasing trend during December to May. On the contrary, the average monthly precipitation of June to November has shown statistically insignificant increment. Seasonally, these areas have experienced a decrement trend during MAM, in which the trend was statistically significant for Hintalo. The decrement amount in Hintalo during the MAM season was 16.343mm per annum. During the JJA season, the trend was increasing and statistically insignificant for all the study areas. Annually, the test showed that only Atsbi has experienced a positive shift in the average amount of annual precipitation; yet Eirop and Hintalo have experienced a decreasing trend with a statistically significant trend for Hintalo. The Sen's Slope here shows that average annual precipitation has been decreasing by 4.098 mm per annum in Hintalo.

Table 3: Mann-kendall test, Sen's Slope and coefficient of variation of the trend in precipitation

Time	Mann-kendall Test			Sen's slope			Coefficient of Variation (%)		
	Atsbi	**Eirop**	**Hintalo**	**Atsbi**	**Eirop**	**Hintalo**	**Atsbi**	**Eirop**	**Hintalo**
January	-0.15	-0.237	-0.225	-1.202	-1.847	-2.195	129.14	130.30	202.51
February	-0.437	-0.536	-0.653	-8.261	-10.323	-12.864	127.66	122.65	180.65
March	-0.111	-0.111	-0.480	-11.408	-11.724	-23.650	98.55	110.94	159.32
April	-0.333	-0.197	-0.444	-13.67	-10.105	-44.807	67.33	80.52	114.76
May	-0.254	-0.229	-0.401	-3.034	-3.217	-10.521	94.18	106.62	128.49
June	0.028	0.111	0.111	4.093	2.046	2.315	130.03	165.74	104.54
July	0.167	0.333	0.000	7.599	9.056	12.444	60.24	68.94	51.68
August	0.00	0.111	0.222	14.746	1.255	24.360	44.43	69.12	51.07
September	0.287	0.237	0.222	16.651	1.867	16.416	108.76	116.84	131.09
October	0.061	0.028	0.111	1.025	0.025	0.1	208.7	240.10	171.00
November	0.222	0.310	0.028	1.225	0.211	0.1	167.97	203.62	208.90
December	-0.237	-0.197	-0.237	-0.125	-3.505	-1.345	211.7	160.71	245.11
MAM	-0.222	-0.267	**-0.556****	-5.386	-6.085	-16.343	52.36	60.30	100.88
JJAS	0.167	0.111	0.278	62.96	16.349	29.887	44.98	56.69	41.31
Annual	0.073	-0.078	**-0.22***	1.462	-1.181	-4.098	31.25	36.61	31.92

In line with this, the variability of the monthly average precipitation depicted in table 3 shows that there was extremely very high variability during all months except for July and August which was relatively much lower than the other months. Seasonally, the coefficient of variation was nearly similar for both MAM and JJAS seasons of Atsbi and Eirop districts. However, the variation during MAM was much higher than JJAS for Hintalo. The coefficient of variation for the annual precipitation was almost similar and high for all the districts, yet it was higher than the regional average, which was 16 percent during 1997 – 2017 (Weldearegay & Tedla, 2018). This implies for a shift from the rainfed to irrigation based agricultural systems. In southern Tigray, the coefficient of variation for the annual precipitation during 1981-2010 was ranging from 33.77 – 233 percent (Hayelom *et al*., 2017). On the other hand, annual precipitation data of 40 years from 109 meteorological stations in Ethiopia showed a coefficient of variation ranging from 20 to 89 percent (Addisu *et al*., 2015).

In order to monitor this precipitation variability, it is crucial to specify the causal factors and study their correlations. The global SST is among the key factor that plays a significant role in determining the variability of the monthly, annual and decadal precipitation patterns. Alhamshry *et al.* (2020) suggested the use of SST of southern Pacific and northern Atlantic oceans as

effective inputs for prediction models of Ethiopian summer and spring rainfalls, respectively. Previous studies confirm that the spatial and temporal variability in the precipitation of Ethiopia is attributed to the variations in SSTs over the Atlantic, Indian, and Pacific Oceanic indices (Degefu *et al*., 2017; Zeleke *et al*., 2017; Dubache *et al.*, 2019; Alhamshry *et al.*, 2020; Molla, 2020; Tefera *et al*., 2020; & Bayable *et al*., 2021).

The strength in the statistical association between Ethiopian precipitation and global SST greatly varies with time and space. In the central and western Ethiopia, the equatorial east Pacific and Indian Ocean SSTs were found to be correlated with JJAS precipitation (Degefu *et al*., 2017). Besides, the drying trend in the southern and northern of Ethiopia is associated with Atlantic Ocean warming and SST of the western Pacific Ocean (Zeleke *et al.*, 2017). Bayable *et al*. (2021) also found that the annual precipitation of eastern Ethiopia was negatively correlated with the SST of Pacific Ocean for JJA while positive for MAM seasons. Further, the SST of central, western and southeastern of Indian Ocean was found affecting the precipitation pattern of western, eastern, northwestern and southeastern parts of Ethiopia (Dubache *et al*., 2019). More importantly, Tefera *et al*. (2020) identified the tropical Indian Ocean as statistically significant drought influencing factor in Ethiopia (Tefera *et al*., 2020).

There was a strong and positive correlation between the precipitation in northeastern Ethiopia and southern Indian, the Atlantic, and most of the western Pacific Ocean (Gobie & Miheretu, 2021). In Tigray region, tropical Indian Ocean was identified as statistically significant drought influencing factor (Tefera *et al*., 2020). The tropical Indian Ocean, tropical Atlantic Ocean, tropical Pacific Ocean, the Red Sea and Nino 3.4 regions were the other drought influencing factors on an annual scale (Tefera *et al*., 2020); and other events like Pacific Decadal Oscillation, Southern Oscillation Index and Indian Ocean Dipole were the important factors for causing meteorological and agricultural droughts in Tigray region (Molla, 2020).

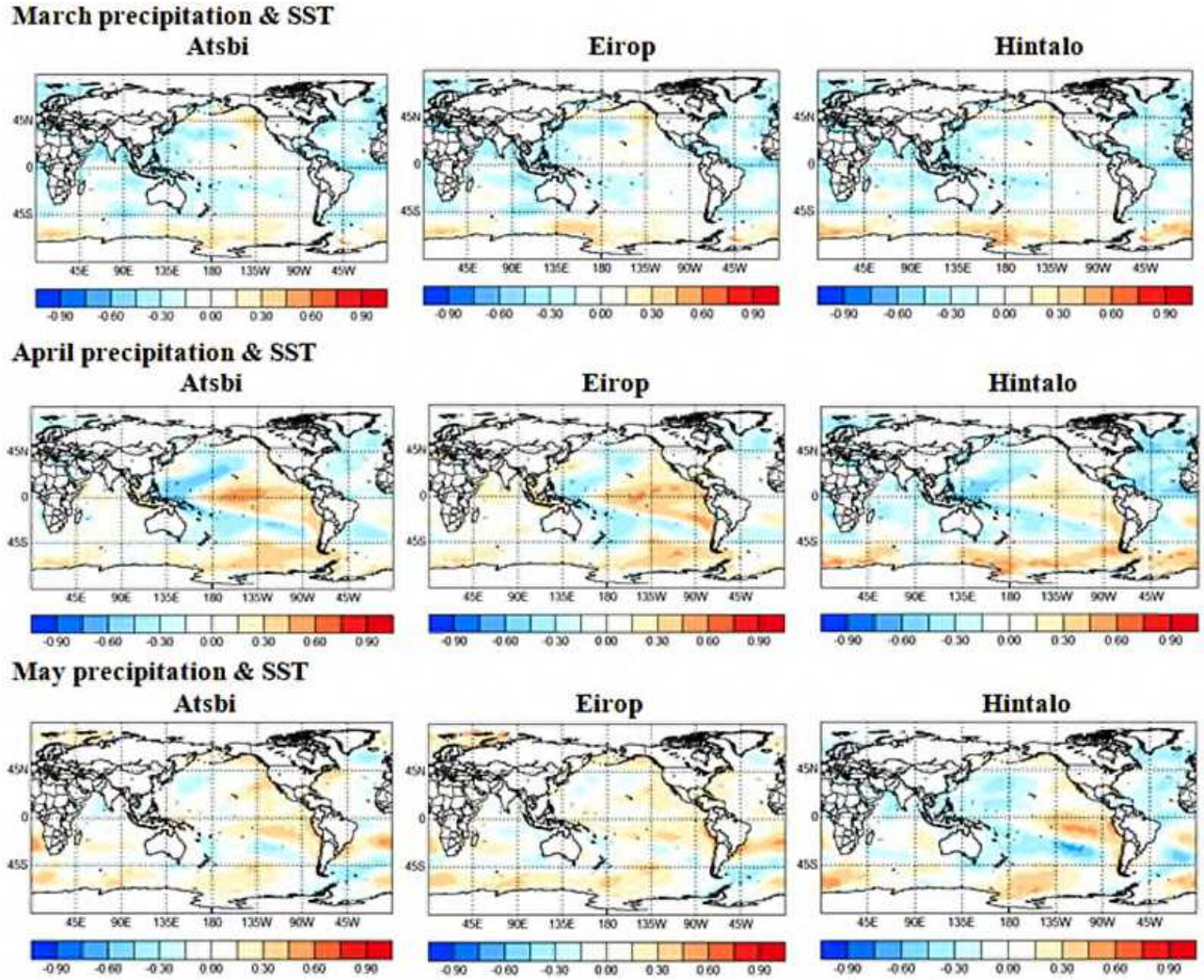
For the reason that many of the correlation analysis made so far were larger in spatial and time scope, a monthly average precipitation of the study areas was used to test for its correlation with the global SST. This is vital in understanding the correlations more in depth.

As shown in figure 6, the canonical correlation analysis shows that the MAM precipitation of the study areas was correlated to the global SST with different correlational values. But, most of these correlations were not strong enough to determine the average monthly precipitation of the

study areas. The central equatorial Pacific Ocean was strongly and positively correlated with April's average precipitation of Atsbi and Eirop. Besides, April's average precipitation of Atsbi and Hintalo was strongly and negatively correlated with the SST of eastern equatorial Pacific Ocean. Further, the April's average precipitation of Hintalo has shown a strong negative correlation with the SST of northeast and northwest equatorial Atlantic Ocean.

This implies that the declined April's average precipitation over Atsbi and Hintalo districts is associated with the warming in the central and eastern equatorial Pacific Ocean. In contrast, the eastern equatorial Pacific Ocean was source of the limited amount of April's precipitation for Atsbi and Hintalo districts. Thus, the projected SST in these regions can be used to predict the precipitation so as to guide food production strategies during the month.

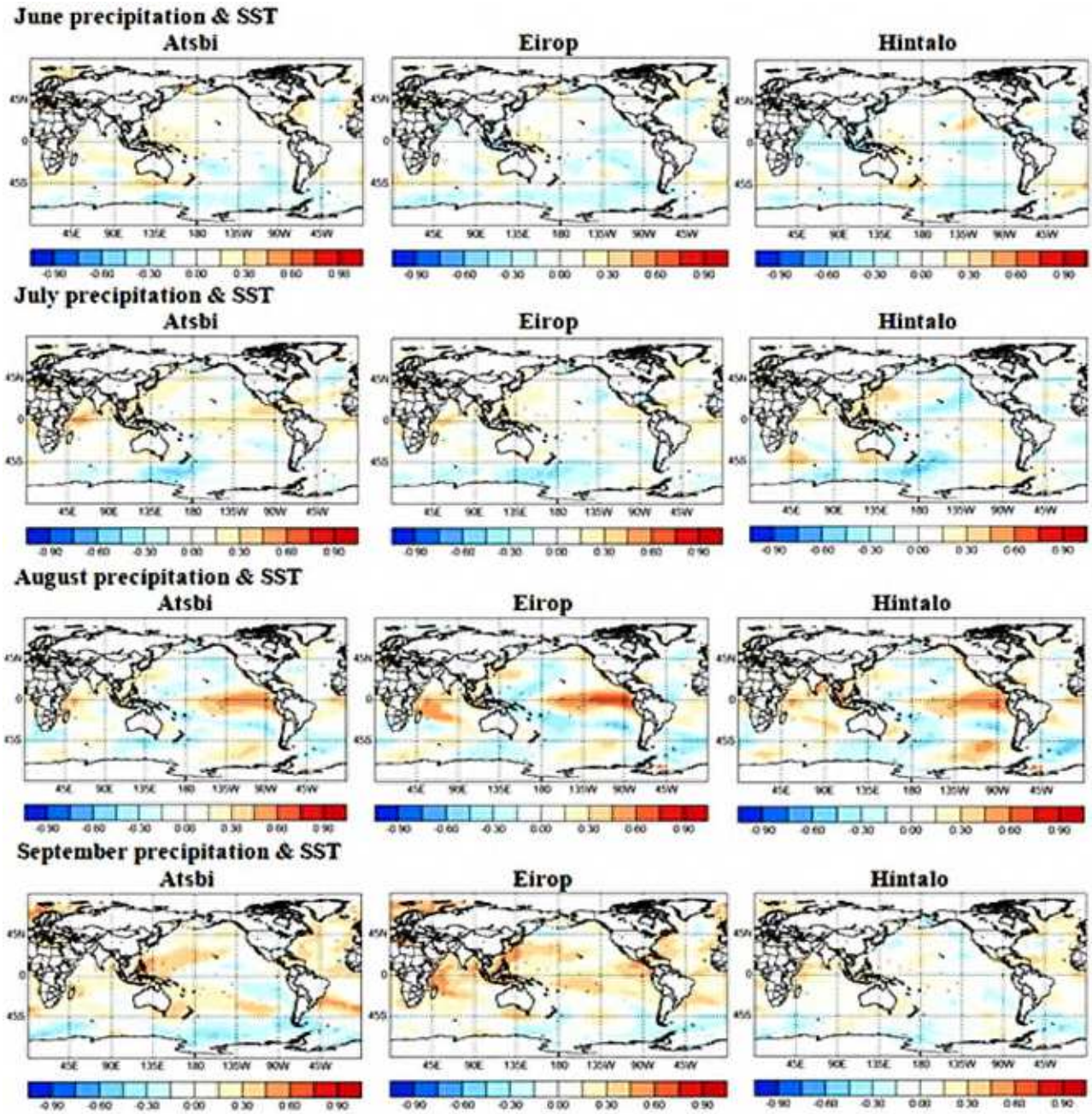
Figure 6: March – May precipitation and its correlation with the global SST



Similar to MAM, the JJAS precipitation of the study areas has shown weak correlation with most of the global SST. Yet, a significant positive correlation was found between August's precipitation all the study areas and SST of the western equatorial Pacific Ocean. The correlation was very strong with Eirop's August precipitation, as shown in figure 7. Thus, the warming in the western equatorial Pacific Ocean is reducing the average August's precipitation of the study areas implying for making informed decisions about food production practices during the month.

Besides, Eirop's August precipitation has shown a strong positive correlation with SST of the south equatorial Indian Ocean. On the other hand, Atsbi's July precipitation was strongly and positively correlated with west equatorial Indian Ocean. Further, September's precipitation of Eirop was found to be strongly and positively correlated with the SST of southwest equatorial Indian Ocean, west equatorial Pacific Ocean, Philippine Sea and South China Sea.

Figure 7: June – September precipitation and its correlation with the global SST



El Niño southern oscillation (ENSO) is a climate phenomenon caused by ocean-atmospheric interaction that occurs mainly in the tropical and sub-tropical Pacific Oceans. This naturally occurring phenomenon is the most predictable climate system at the time scales from months to seasons and years (Tang *et al.*, 2018), providing the basis for regional and local level precipitation predictions.

ENSO has a significant climate influence on climate patterns of various parts of the world including Ethiopia. Although the different parts of Ethiopia have different climate sensitivities, the 2015 drought that occurred in most parts of the country and East Africa was associated with ENSO induced rain shortages (Philip *et al.*, 2018; & Bayable *et al.*, 2021). In northern Ethiopia, periodicity in dryness and wetness were largely determined by ENSO variability in both the spring and summer rainy seasons (Zeleke *et al*., 2017).

In northeast part of Ethiopia, La Nina was associated with increased rainfall in most parts of the region and that El Nino's was associated with decreased rainfall in limited parts of the region (Gobie & Miheretu, 2021). In Tigray region, in addition to the global SST indices, ENSO was identified as drought influencing factor (Molla, 2020 & Tefera et al., 2020). Similarly, Looby (2019) stated that El Nino has intensified the severe and prolonged drought that has occurred in Tigray in the last 4 to 5 decades, as shown during 2015-2016 El Niño.

As shown in table 4, the effect of ENSO in most rainy months of the study areas was negligible. Nevertheless, JFM and FMA ENSO indices were associated with decreased April's precipitation of Atsbi and Eirop very significantly (P<0.01). Besides, FMA and MAM ENSO indices were associated with decreased May's precipitation of Hintalo significantly (P<0.05). On the other hand, MJJ ENSO indices was significantly associated with increased July's precipitation of all the study areas (P<0.05). Thus, relevant bodies are supposed to have projected ENSO data of JFM, FMA, MJJ and MAM in advance for guiding food production activities of the study areas.

Table 4: the correlation between the study areas precipitation and the global ENSO

STD Precipitation		STD_ENSO							
		DJF	JFM	FMA	MAM	AMJ	MJJ	JJA	JAS
March	Atsbi	0.118	0.109						
	Eirop	0.082	0.080						
	Hintalo	0.068	0.055						
April	Atsbi		**0.461****	**0.449****					
	Eirop		**0.447****	**0.440****					
	Hintalo		0.267	0.271					
May	Atsbi			0.202	0.255				
	Eirop			0.203	0.250				
	Hintalo			**0.313***	**0.331***				
June	Atsbi				-0.042	-0.032			
	Eirop				-0.175	-0.148			

	Hintalo				-0.099	-0.018			
July	Atsbi					-0.198	**-0.345***		
	Eirop					-0.295	**-0.391***		
	Hintalo					-0.286	**-0.341***		
August	Atsbi						-0.076	-0.212	
	Eirop						0.120	-0.029	
	Hintalo						-0.015	-0.156	
September	Atsbi							-0.190	-0.197
	Eirop							-0.196	-0.256
	Hintalo							-0.296	-0.270

Conclusion

Food security depends on the four pillars: food availability, access, utilization and stability. And lack of adequate precipitation and its variability is among the main causes of food insecurity. Nevertheless, food availability is mostly dependent on precipitation compared to the other pillars, particularly in areas where the farming system is dominantly rainfed.

The study areas have showed a similarity in the magnitude and seasonality of precipitation. March – May and June – September were the wettest seasons of the study areas. While the March – May average precipitation of the study areas have showed a decreasing trend, an insignificant increment was observed in the precipitation pattern of June – September. This implies for careful decisions to be made for any agricultural practices during these seasons.

On the other hand, a marked variation was observed in the trend of the precipitation pattern among the study areas. Although no significant trend was detected for Atsbi and Eirop precipitation pattern, a very significant decline in the trend of March – May average precipitation and a significant decline trend in the annual average precipitation of Hintalo area is observed. This calls for an immediate action to get alternative sources of water for the rural areas where precipitation is the only source for food productions.

More importantly, not all of the rainy months of the study areas were significantly susceptible to the global SST and ENSO variations. The April's average precipitation of the study areas is found being under the influence of central and eastern equatorial Pacific Ocean and northeast and northwest equatorial Atlantic Ocean SSTs. Further, the SST of south, west, and southwest of equatorial Indian Ocean, and west equatorial Pacific Ocean were associated with July – September average precipitation with greater variation in strength among of the study areas.

The ENSO indices, on the other hand, are found to be significantly unrelated with many of the rainy seasons of the study areas. Nevertheless, July's average precipitation of all the study areas, April's average precipitation of Atsbi and Eirop, and May's precipitation of Hintalo are found significantly associated with the ENSO indices. Therefore, SSTs of central and eastern equatorial Pacific Ocean, northeast and northwest equatorial Atlantic Ocean, southwest of equatorial Indian Ocean, and west equatorial Pacific Ocean, and the ENSO indices of JFM, FMA, MJJ and MAM can be used to develop a skillful precipitation forecast for the areas under the study.

Generally, the limited amount of precipitation, given its higher degree of variability, will be the major challenge in the task of achieving food security in the food insecure rural areas. Therefore, unless coping strategies are arranged that meet the varying monthly, seasonal and annual precipitation, or alternative water sources are used and the rain water is harvested prudently, these areas will continue to face the severe consequences of food insecurity.

Furthermore, the precipitation pattern and its statistical association with the SST and ENSO indices vary greatly in strength among the study areas. Thus, future researchers have to analyze precipitation patterns and any associations with their trend in clusters rather than as a whole. In this way, food security programs and actions can be effectively downscaled to the local level based on their respective precipitation pattern information.

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