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Seasonal and Annual Rainfall Trend Detection in Eastern Amhara, Ethiopia

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ABSTRACT

Precipitation is one of the most important climate variables that could influence the climatological, agricultural, and hydrological studies. This paper presents several test statistics to detect the effects of autocorrelation and its level of significance in the seasonal rainfall data over eastern Amhara. The daily rainfall data was obtained from the National Meteorological Agency of Ethiopia. The Mann-Kendall test, Sen's slope estimator, and Pettit's test were used to assess the significance, magnitude, and point changes in the seasonal rainfall data, respectively. The effects of autocorrelation in the time series data was no found significantly, except at lag 1. The Mann-Kendall test revealed that 65% of study sites showed an increasing trend with only 31% was statistically significant ($p<0.05$) during the Annual season. About 85% of the study sites showed an increasing trend with 41% of it was significant during the Kiremt season. On the other hand, 70% of the study site during Bega seasons showed increasing trend with only 21% part of it was statically. Similarly, during Belg seasons, 35% of the study sites were in an increasing trend, in which 14% was significant. In this study, the effects of autocorrelation and seasonal change points were not detected in the time series data.

Keywords: Rainfall; Trend analysis; Eastern Amhara; Ethiopia

INTRODUCTION

Precipitation has changed significantly in different parts of the globe during the 20th century [1]. Literature states that the coming decades will have experienced in the higher change in precipitation intensity [2,3]. Developing countries in East Africa like Ethiopia may experience greater variability of precipitation and evapotranspiration [4]. Changes in precipitation patterns influence runoff, soil moisture, and ground-water and may lead to floods, droughts, loss of biodiversity, and agricultural productivity. The fluctuation of the temporal distribution of rainfall also impacts on cropping pattern and productivity, which resulted in food insecurity [5]. The distribution, amount, seasonal cycle, onset and cessation times of rainfall, and the length of the growing season are showing strong variation across the country in Ethiopia [6,7]. Rainfall in Ethiopia often erratic, and associated with droughts and have been major causes of food shortages and famines [8,9]. According to Von Braun, for instance, a decreasing of 10% in seasonal rainfall from the long-term causes a 4.4% reduction of food production in Ethiopia [10]. The decline of annual and Kiremt rainfall in eastern Ethiopia was observed since 1982 and since 1996 [11,12]. On the other, Conway reported that there are no recent trends in rainfall over the north eastern Ethiopian highlands [13]. Most studies in Ethiopia emphasized on analysis of trends in annual and seasonal rainfall totals and intra-seasonal rainfall variability such as the timing of season start date and season end date, the number of rainy and dry days, and dry spells, but failed to observe the effects autocorrelations, testing of significance, independency, and stationary of in the entire time series data [14-16].

The detection of seasonal trends is mostly computed using parametric and non-parametric statistical tests. However, non-parametric methods have higher power or efficiency than a parametric approach [17]. The corresponding estimated magnitude may be a Sen's slop [17]. Approaches of modified Mann–Kendall (MMK) include Pre-Whitening (PW), Trend-Free-Pre-Whitening (TFPW), TFPW cu, and Long-Term Persistence (LTP) are applied abundantly in trend analysis researches [18-21]. The Pettit's test and Mann–Kendall (MK) test have been used in several studies to find out trends in time series of rainfall data.

The need for trend analysis becomes the research agenda because the components of rainfall trends such as seasonality, cyclic, stationary,

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and the horizontality of time series rainfall data are become fluctuated due to change in climate [22]. An understanding of the temporal variation of rainfall should be developed by studying the trend of rainfall data for longer periods. The spatial and temporal trends of precipitation results are an important for climate analyst and water resources planner. The objectives of this study were to observe the effects of autocorrelation in the seasonal and annual rainfall series and detecting the behaviour of trends, i.e. directions, significance, magnitude, and change point of trends in seasonal and annual rainfall series.

MATERIALS AND METHODS

Study area description

The study was conducted in the eastern Amhara, Ethiopia. Amhara Regional State is one of the parts of Ethiopian Federal Government. It is located in between 8.72°N -13.25°N latitude, and 38.33°E-40.29°E longitudes (Figure 1). The topography of the region is mostly characterized by a chain of mountains, hills, and valleys ranging from 1379 m-3809 m above sea level (masl). The Region has a bimodal rainfall pattern, including the main rainy season, which is called Kiremt (summer) season extends from June to September, and short rainy season, which is called Belg (spring) from February to May. According to current studies, on average annual rainfalls are ranging between 516.9 mm to 1342 mm in the study sites. At the seasonal scale, it receives 400 mm-1035 mm, 26 mm-327 mm, and 8 mm-136 mm in Kiremt, Belg and Bega seasons, respectively. The Eastern Amhara is known for its recurrent drought occurrences and it is one of the most food-insecure areas in the Amhara Regional State [8,23-25]. The Region is categorized by four agro-ecological zones, namely, Wurch, highland, mid-latitude and low land covering 0.64%, 16.25%, 46.28% and 36.83% of the area respectively [26]. The area is characterized by erratic rainfall and low crop productivity [27]. The dominant soil type in the study areas is Verti soil with different classifications: Eutric Vertisols, Calcic Vertisols and Dystric Vertisols [26,28-31].

Table 1: Geographical locations of 20 weather stations for the study sites.

Sites	Latitude °N	Longitude °E	Altitude (m)
Alemketema	10.03	39.17	2204
Ambamariam	11.2	39.22	2990
Amdework	12.43	38.71	2561
Bati	11.19	40.02	1502
Cheffa	10.86	39.77	1466
Debrebirhan	9.67	39.51	3202
Enewari	9.83	39.15	2667
Gundomeskel	10.18	39.86	2504
Kobo	12.13	39.63	1468
Kombolcha	11.08	39.72	1857
Lalibela	12.04	39.04	2487
Majete	10.5	39.85	1573
Mehalmeda	10.31	39.66	3084
Mekaneselam	10.74	38.76	2605
Shewarobit	10.01	39.89	1277
Sholagebeya	9.22	39.55	2839
Sirinka	11.75	39.61	1861
Tisiska	12.78	38.8	1469
Wereilu	10.58	39.44	2708
Wogeltena	11.59	39.22	2952

Data analysis

This study covered the time scale of June to September (Kiremt), October to January (Bega), February to May (Belg) and over all annual seasons [32]. The daily observed rainfall data (1986-2018) were collected from the National Meteorological Agency of Ethiopia (NMA), Eastern Amhara Meteorological Center. About 20 station's gauge data were used. Some station's data were missing, and extreme outliers were existed for certain months and/or years. In the purpose of data quality control, the time series

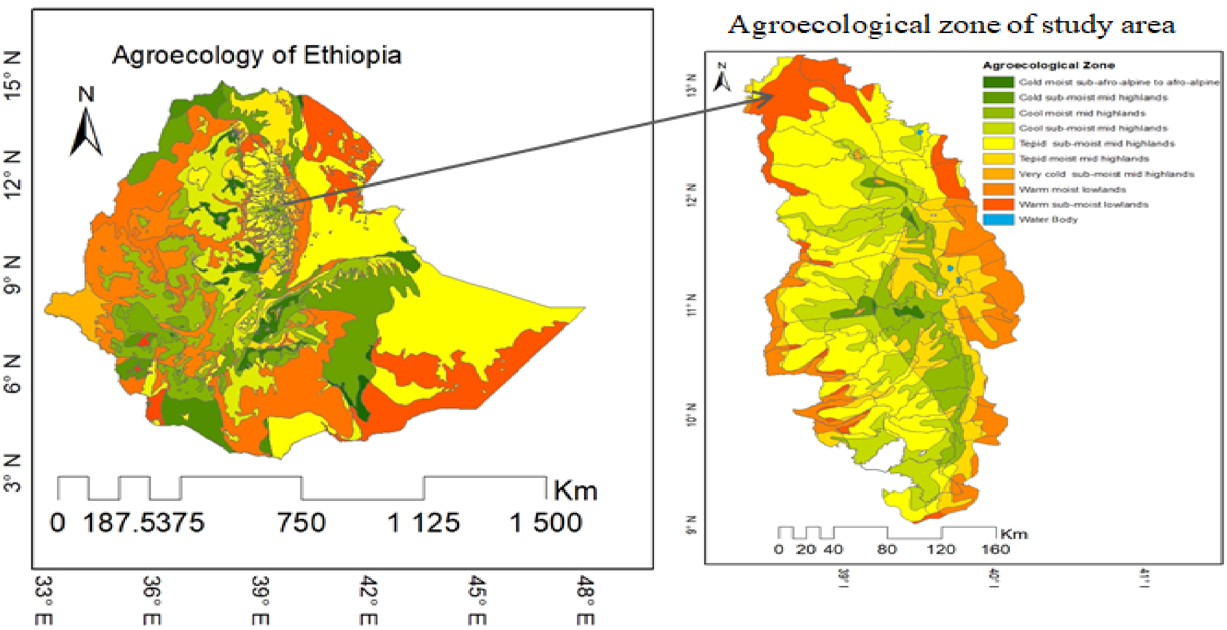

Figure 1: Agro-ecological zone of the study area.

rainfall data were checked if the missing data and outliers were existed using Amelia viewer package in R analytical tools [33]. In multiple imputations for missing value, it was concerned with the complete data parameters as θ=(μ,Σ). The equation of the model of the data as follows:

$$p(D^{obs} \mid \theta) = \int p(D \mid \theta) dD^{mis} \quad \text{(Equation 1)}$$

Where D^{obs} was observed part, D^{mis} was an unobserved part, and D was imputation dataset which has a multivariate normal distribution with mean vector μ and covariance matrix S. With this likelihood on θ was as:

$$p(\theta \mid D^{obs} \propto D^{obs} \mid \theta) = \int p(D \mid \theta) dD^{mis} \quad \text{(Equation 2)}$$

Once the complete data parameters are drawn, it could make imputations by drawing values of D^{mis} from its distribution conditional on D^{obs} and the draws of θ, which was a linear regression with parameters that can be calculated directly from θ.

The trends of seasonal and annual rainfall were analyzed by using non-parametric methods [34]. The non-parametric Mann–Kendall (MK) statistical test was used to test the significance of the trend, while the Theil-Sen's Slop Approach (TSA) was used to quantify the magnitude of rainfall trend [35-38]. All statistical parameters were computed using R version 3.6.1. R is an environment incorporating programming language, which is powerful, flexible, and has excellent graphical facilities [39]. Because the R system is open source, it has started to become the main computing engine for statistical research [40-43].

Detection of autocorrelation

The challenge in hydrological data analysis and interpretation is the confounding effect of serial dependence [44]. The precondition in trend analysis is testing of the effect of autocorrelation. In this study, the time series data were tested for randomness and independence using the autocorrelation function(r_k) as described in Box and Jenkins [45]. The autocorrelation r_1 measures the relationship between X_i and X_{i-1}, r_2 measures the relationship between X_i and X_{i-2}, and so on. The value r_k can be written as

$$r_k = \frac{\sum_{i=1}^{n-1} (X_i - \overline{X})(X_{i+1} - \overline{X})}{\sum_{i=1}^{n} (X_i - \overline{X})^2} \quad \text{(Equation 3)}$$

Where X_i is an observation, X_{i+1} is the following observation, $\overline{X}$ is the mean of the time series, and n is the length of the time series of data. According to Salas, and most recent study like Gocic and Trajkovic defined the critical region for testing the time series data sets of serial correlation using the following equation [46,47].

$$r_k = \frac{-1 - 1.645\sqrt{(n-2)}}{n-1} \leq 1 \leq \frac{-1 + 1.645\sqrt{(n-2)}}{n-1} \quad \text{(Equation 4)}$$

If r_k falls inside the above interval, then the time series data sets are independent observations, while in cases where r_k is outside the above interval, the data are serially correlated. If time series data sets are independent, then the MK test and the TSA can be applied to the original values of time series. If time-series data sets are serially correlated, then the 'pre-whitened' time series may be used [44,47]. It is common to find autocorrelation in residuals in the time series data. Ljung-Box test was used to test the serial correlation in the residuals of time series data. A small p-value indicates there is significant autocorrelation remaining in the residuals of time series data. In general, the assumption of independence is violated if autocorrelation is present in the series of data [48].

The Mann-Kendall's test

Mann-Kendall test method was employed to detect the significance of seasonal and annual rainfall trends. In most trend analysis study, the Mann-Kendall's test was mostly used due to less sensitive to outliers and used without specifying whether the trend is linear or nonlinear [44].

$$S = \sum_{i=1}^{n-1} \sum_{j=i+1}^{n} \operatorname{sgn}(X_j - X_i) \quad \text{(Equation 5)}$$

Where,

$$\operatorname{sgn}(X_j - X_i) = \begin{cases} 1 & X_j < X_i \\ 0 & X_j = X_i \\ -1 & X_j > X_i \end{cases} \quad \text{(Equation 6)}$$

Where X_j and X_i are the sequential precipitation values in months j and i (j> i) and *N* is the length of the time series. If two or more data points have the same value consecutively, then it is said that a tie has occurred. If there are no ties, the variance Var (S) is computed as follows:

$$Var(s) = \frac{n(n-1)(2n-5)}{18} \quad \text{(Equation 7)}$$

If there are ties, then the variance Var (S) is computed as follows:

$$Var(s) = \frac{n(n-1)(2n-5) - \sum_{j=j}^{J} t_j (t_j - 1)(2t_j + 5)}{18} \quad \text{(Equation 8)}$$

Where J is the number of tied groups of repeated values and t_j is the number of repeated values in the j^{th} group. The standard normal Z_{MK} test statistic is computed as follows [44].

$$Z_{MK} = \begin{cases} \dfrac{S-1}{\sqrt{\operatorname{var}(s)}} & S > 0 \\ 0 & S = 0 \\ \dfrac{S+1}{\sqrt{\operatorname{var}(s)}} & S < 0 \end{cases} \quad \text{(Equation 9)}$$

In two-sided test for trend, the null hypothesis *Ho* should be accepted if $|Z_{MK}| <$ Z1-α/2 at a given level of significance. Z1-α/2 is the critical value of Z_{MK} from the standard normal table. For this study, the null hypothesis was rejected at 5% significance level, which has Z value is 1.96.

Sen's slope estimator test

The magnitudes of trends (T_i) in mm per season was computed by using the Sen's slope method [38]. This test is applied in cases where the trend is assumed to be linear, depicting the quantification of changes per unit time.

$$T_i = \frac{X_j - X_k}{j - k} \quad \text{(Equation 10)}$$

Where X_j and X_k are considered as data values of time j and k (j>k) correspondingly for i =1, 2.....N, the median of these N values of T_i is represented as Sen's estimator (Qi) of the slope which is given as

$$Q_i = \begin{Bmatrix} \frac{1}{2}\left(T\frac{N}{2}+T\frac{N+2}{2}\right), & if\ N \text{ is even} \\ T\frac{N+1}{2} & , if\ N \text{ is odd} \end{Bmatrix} \quad \text{(Equation 11)}$$

Pettit's test

Mann–Whitney Pettitt's non-parametric test (K_T) was applied for detecting change points in the seasonal and annual time-series data [49]. Hamed proposed a pre-whitening technique in which the slope and lag-1 serial correlation coefficient are simultaneously estimated [50]. The lag-1 serial correlation coefficient is then corrected for bias before pre-whitening. The change-point of the series is located at K_T, and provided that the statistic is significant for p <0.05. The non-parametric statistic is defined as:

$$K_T = \max\left|\text{Ut,T}\right| \quad \text{(Equation 12)}$$

Where,

$$Ut,T = \sum_{i=1}^{t}\sum_{i=j+1}^{T}\text{sgn}(X_i - \overline{X}) \quad \text{(Equation 13)}$$

Buishand range test

The homogeneity of the time series data was tested based on the adjusted partial sums or cumulative deviations from the mean [51]. Let x denote a normal random variation, then the following model with a single shift (change-point) can be proposed as:

$$X_i = \begin{Bmatrix} \mu + \varepsilon_i & i = 1..........m \\ \mu + \Delta + \varepsilon_i & i = m+1.......n \end{Bmatrix} \quad \text{(Equation 14)}$$

ε ⁿN (0,σ). The null hypothesis Δ=0 is tested against the alternative Δ≠ 0.

In the Buishand range test, the rescaled adjusted partial sums are calculated as:

$$Sk = \left(\sum_{i=1}^{t}(X_i - \overline{X}) \quad 1 \le i \le n\right) \quad \text{(Equation 15)}$$

The test statistic is calculated as:

$$Rb = \frac{\max Sk - \min Sk}{\delta} \quad (0 \le k \le n) \quad \text{(Equation 16)}$$

The critical values calculated by Buishand range test were determined at 5% probability levels.

RESULTS AND DISCUSSION

Seasonal rainfall distribution

The time series of Annual, Kiremt, Bega, and Belg rainfall seasons are shown in Figure 2 after the quality data control was performed. The finding indicated the eastern parts of Amhara experienced with a bimodal rainfall pattern, where much of the rainfall concentrated in the main rainy season (Kiremt), and a small amount of rainfall occurred during the second rainy season (Belg) whereas the Bega season is relatively dry [31,52]. The graphical presentation of any data series is able to describe the data to be visible, and to identify the patterns, distribution, unusual observations, changes over time, and relationships between variables.

The three components of the seasonal data series are shown in Figure 3. Notice that the seasonal components were changed slightly, but around 4^{th} year showed far apart from the normal seasonal patterns. Similarly, the sudden fall or unusual observation was observed at the end of 2017 in the random (error) component. The random (error) component in the bottom panel is the seasonal and trend-cycle components that have been subtracted from the data. The additive decomposition of data presentation is the most appropriate method if the magnitudes of the seasonal fluctuations have existed [53,54].

Autocorrelation

The time series data of Annual, Kiremt, Bega, and Belg seasons are presented in Figures 4-7 respectively. The time plot shows some changing variation at the beginning and end of the seasons, but was a relatively stable pattern in between. The histogram showed that the residuals seem to be slightly skewed, mean the residuals slightly varied with constant values. The autocorrelation plot shows a significant negative spike at lag 1 and crossed the signature line, but it is not quite enough to say the overall Ljung-Box test to be significant at the 5% significant level. The dashed blue lines indicate whether the correlations are significantly different from zero. Although the significant autocorrelation was persisted at lag

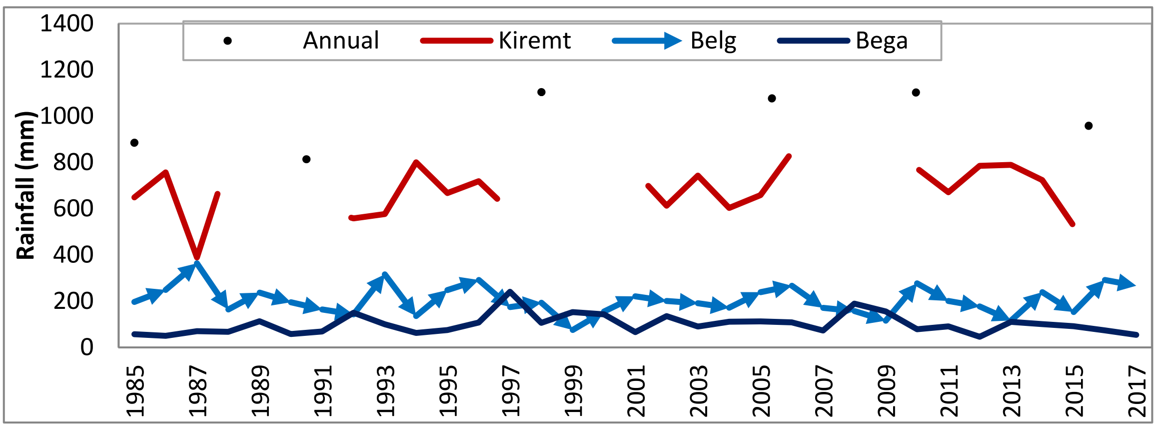

Figure 2: Rainfall totals (mm) for Annual, Kiremt, Bega, and Belg seasons.

1, the bar plot shown decreased within the confidence interval throughout the time lags. One should notice the interpretation of the "significance" of the correlation at various lags need care because at least one approximate, out of total observations may happen correlations with significant, like this study, in which the significant level has occurred at lag 1 (Figures 4-7). The autocorrelation of r_1 at lag 1 was higher negative, even it cut the lower significant line (significant autocorrelation), while the other autocorrelation coefficients fluctuated positively and negatively, but inside the significant line (non-significant autocorrelation). The rational implication of ACF functions is used for model criticism, mean to test if there is structure left in the residuals.

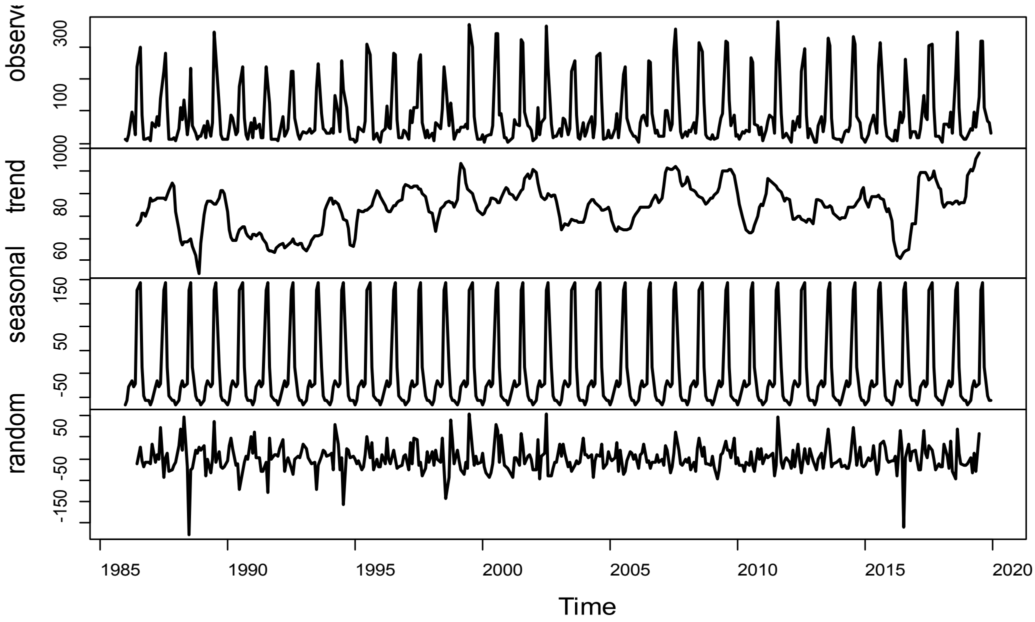

Figure 3: Components of seasonal rainfall (mm) (random or error, seasonal, trend, and original data distribution).

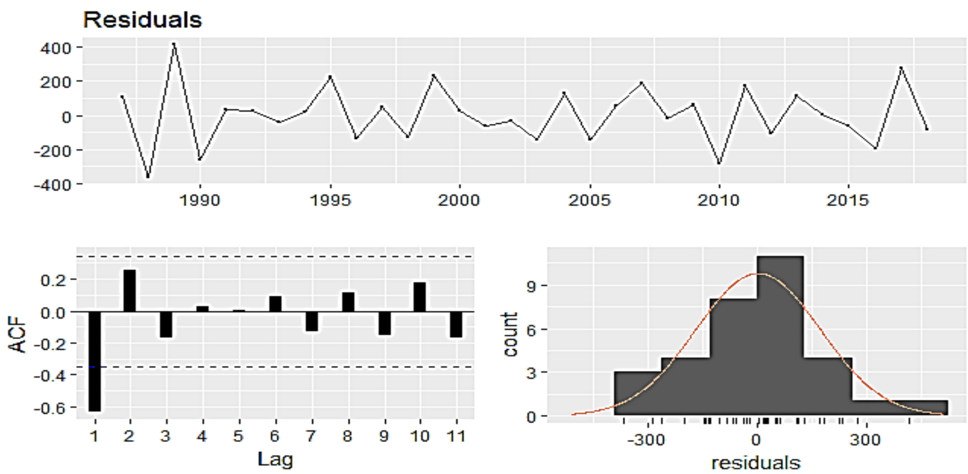

Figure 4: The ACF of Annual rainfall residuals for the period (1985-2018).

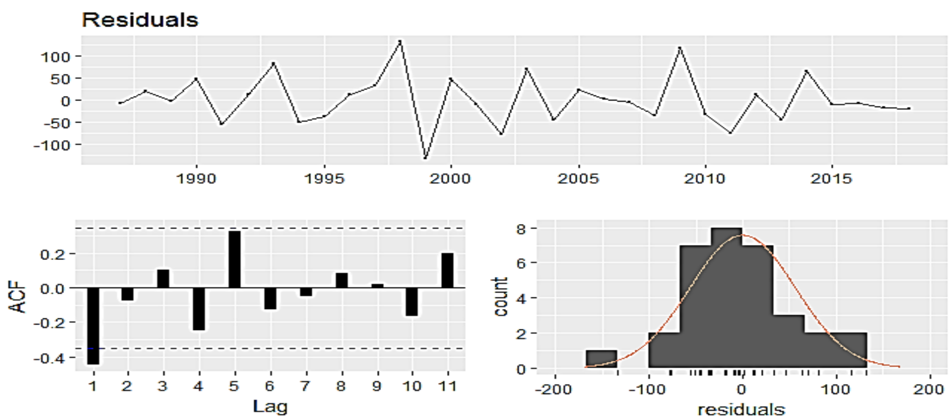

Figure 5: The ACF of Kiremt rainfall residuals for the period (1985-2018).

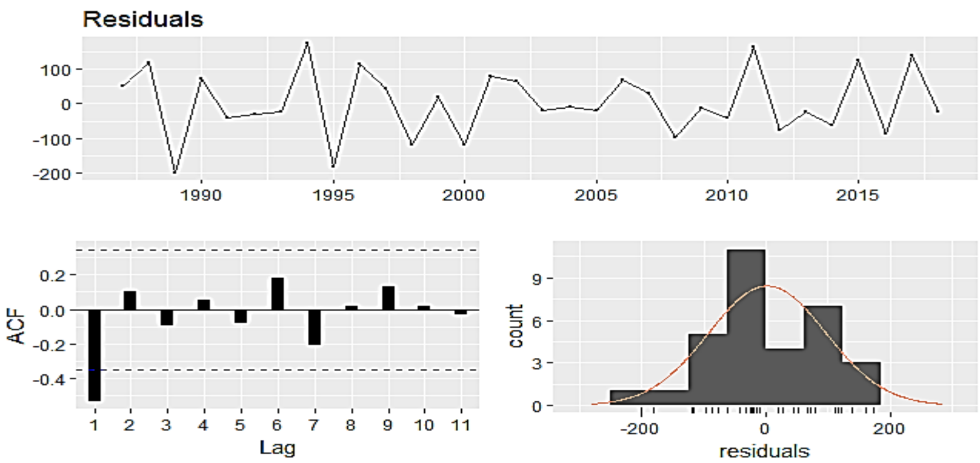

Figure 6: The AC of Bega rainfall residuals for the period (1985-2018).

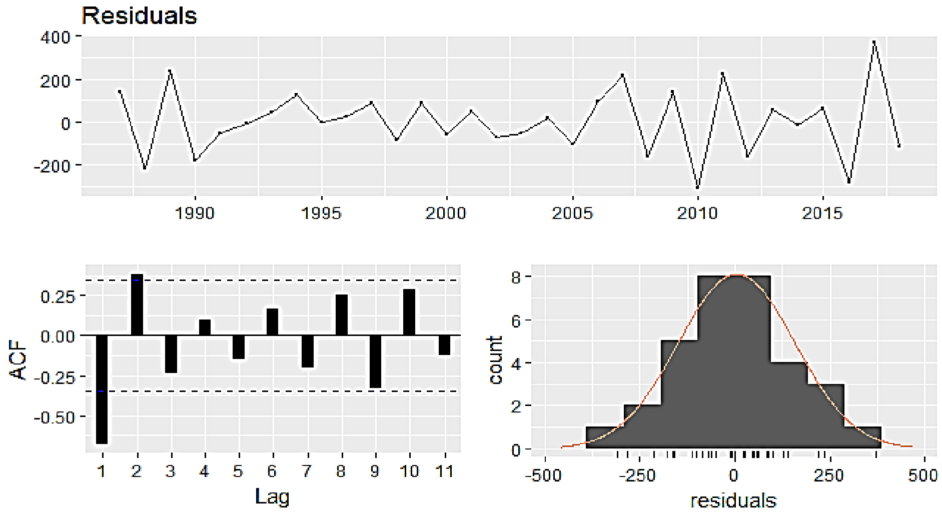

Figure 7: The ACF of Belg rainfall residuals for the period (1985-2018).

1, the bar plot shown decreased within the confidence interval throughout the time lags. One should notice the interpretation of the "significance" of the correlation at various lags need care because at least one approximate, out of total observations may happen correlations with significant, like this study, in which the significant level has occurred at lag 1 (Figures 4-7). The autocorrelation of r_1 at lag 1 was higher negative, even it cut the lower significant line (significant autocorrelation), while the other autocorrelation coefficients fluctuated positively and negatively, but inside the significant line (non-significant autocorrelation). The rational implication of ACF functions is used for model criticism, mean to test if there is structure left in the residuals.

The stationary of all-season from 1985 to 2018 was checked by the Ljung-Box test and all the series were found to be stationary. All statistical parameters that explain the significance of observed data are shown in Table 2. The common method to test the time series data are the ARIMA (0, 0, 0), ARIMA (0, 1, 0), ARIMA (0, 0, 1) and ARIMA (0, 1, 1). These simple linear models are based on the Akaike Information Criteria (AIC) and Bayesian Information Criteria (BIC). For developing the potential predictive model, the priority is given for the basis of minimum values for AIC and BIC. From Table 2, the ARIMA (0, 1, 1) model has minimum values of AIC and BIC for Kiremt, Bega, and Belg seasons whereas ARIMA (1, 1, 0) for Annual season (Table 2). Mean Absolute Percentage Error (MAPE) is the value of error in the ARIMA forecast model. A forecast "error" is the difference between an observed value and its forecast. Therefore, the error percentage was varied between 8-14% for Annual, 13-15% for Kiremt, 30-36% for the Bega, and 28-36% for Belg seasons in all ARIMA models. In this study, any ARIMA model was not recommended because there was no a significant change in the data series to develop potential predictive models.

Table 2: Statistical parameters of ARIMA models for the seasonal time series data.

ARIMA models		Seasons			
	Statistical Parameters	Annual	Kiremt	Bega	Belg
ARIMA (1, 1, 1)	ACI	397.2	402.46	339.6	365.9
	BCI	401.57	406.85	344	370.3
	MAPE	8	13.99	30.77	31.14
	ACF	0	-0.14	-0.03	-0.05
	P-value	0.7	0.81	0.52	0.68
ARIMA (0, 1, 1)	ACI	401.4	401.4	337.7	364
	BCI	399.9	404.3	340.6	367
	MAPE	14.3	14.3	30.83	31.2
	ACF	-0.19	-0.18	-0.01	-0.1
	P-value	0.69	0.67	0.67	0.79

ARIMA (0, 0, 1)	ACI	408.6	412.9	346.29	372.4
	BCI	414.1	417.4	350.78	377
	MAPE	8.95	15.5	35.86	28.4
	ACF	0.01	-0.06	0	0
	P-value	0.18	0.57	0.47	0.79
ARIMA (1, 0, 0)	ACI	409.5	412.9	346.2	372.4
	BCI	414	417.4	350.8	376.9
	MAPE	8.92	15.5	35.79	28.51
	ACF	-0.03	0.01	0	-0.01
	P-value	0.18	0.57	0.47	0.79
ARIMA (0, 0, 0)	ACI	407.7	410.92	344.97	370.7
	BCI	410.6	413.9	347.9	373.6
	MAPE	8.97	15.54	36.26	29.02
	ACF	0.06	0	0.14	-0.08
	P-value	0.27	0.69	0.64	0.86
ARIMA (1, 1, 0)	ACI	395.4	406.3	344.8	374.2
	BCI	398.3	409.3	347.7	377.2
	MAPE	7.95	14.75	36.28	33.92
	ACF	-0.06	-0.14	-0.16	-0.15
	P-value	0.87	0.45	0.18	0.37

Note: ACF: Autocorrelation Function; AIC: Akaike Information Criteria; BIC: Bayesian Information Criteria; MAPE: Mean Absolute Percentage Error.

Rainfall trend analyses

The overall results in all stations revealed a clear pattern of negative and positive trend, as well in different significant levels (Table 3). In the annual time scale, approximately 35% of the study sites showed a negative trend, but only 33% of it was significant ($p < 0.05$) (Table 3). The remaining 65% of the case study had an increasing trend with only 31% part of it was statistically significant. In the case of Kiremt season, only 15% of the study sites showed decreasing tend, of which 33% was statistically significant. The majority part of the study sites (85%) showed an increasing trend with 41% of it was a significant during the Kiremt rainfall season. When we look at the Bega season, 70% of the case study showed an increasing trend, but only 21% part of it was significant. In contrast, 30% of the cases study showed a decreasing trend with a non-significant level ($p > 0.05$) (Table 3). The most part of the study sites (around 65%) during Belg season showed a decreasing trend, in which only 15% of it was statistically significant. The remaining 35% had been in increasing trend; with only 14% of it was statistically significant. Woldeamlak B. and Conway found that the Kiremt rainfall showed a significant increasing trend at Dessie and Labella whereas a significant decreasing trend was observed at Debre Tabor [52,55].

Subsequently, the magnitude change of rainfall trend and directions were showed highly varied at each site (Figures 8 and 9). The Mann-Kendall z-value (Zmk) explained whether the time series data are in increasing or decreasing trend (i.e., direction), while the Sen's

Table 3: Summary of statistical parameters.

	Kiremt			Bega			Belg			Annual		
Site code	ZMK	Sig.	Q	ZMK	Sig.	Q	ZMK	Sig.	Q	ZMK	Sig.	Q
Alemketema	-0.08	Ns	-0.56	0.48	Ns	0.48	-0.81	Ns	-1.19	0.46	Ns	0
Ambamariam	1.53	Ns	5.56	1.46	Ns	0.84	0.68	Ns	0.96	1.66	Ns	0.02
Amdework	2.18	Sig.	6.49	-0.56	Ns	-0.33	-0.23	Ns	-0.37	-0.39	Ns	0
Bati	2.15	Sig.	6.49	-0.4	Ns	-0.32	-0.85	Ns	-1.9	0.05	Ns	0
Cheffa	1.44	Ns	4.98	0.98	Ns	0.95	1.16	Ns	2.37	1.87	Ns	0.03
Debrebirhan	1.35	Ns	3.16	-0.11	Ns	-0.07	-0.25	Ns	-0.33	0.33	Ns	0
Enewari	2.77	Sig.	11	2.03	Sig.	0.73	2.38	Sig.	4.36	2.9	Sig.	0.04
Gundomeskel	2.12	Sig.	5.97	1.59	Ns	0.48	1.92	Ns	2.63	2.22	Sig.	0.03
Kobo	1.22	Ns	3.46	-0.57	Ns	-0.43	0	Ns	-0.06	0.19	Ns	0
Kombolcha	0.76	Ns	2.48	0.2	Ns	0.21	1.64	Ns	-3	-0.46	Ns	-0.01
Lalibela	3.05	Sig.	7.24	2.49	Sig.	1.67	-2.89	Sig.	-6.85	0.11	Ns	0
Majete	1.56	Ns	5.8	0.2	Ns	0.33	-1.19	Ns	-2.95	0.08	Ns	0
Mehalmeda	2.45	Sig.	7.37	1.75	Ns	0.76	-0.45	Ns	-0.57	2.6	Sig.	0.03
Mekaneselam	0.51	Ns	1.02	0.33	Ns	0.35	0.54	Ns	0.74	0.49	Ns	0.01
Shewarobit	0.53	Ns	1.88	0.36	Ns	0.57	-0.2	Ns	-0.37	-0.19	Ns	0
Sholagebeya	-1	Ns	-3.83	0	Ns	-0.01	-1.81	Sig.	-2.81	-0.35	Ns	0
Sirinka	1.53	Ns	4.41	1.38	Ns	1.76	-0.03	Ns	-0.08	2.17	Sig.	0.05
Tisiska	-2.46	Sig.	-5.92	-1.66	Ns	-0.62	-1.19	Ns	-1.53	-2.52	Sig.	-0.02
Wereilu	2.62	Sig.	6.74	-0.57	Ns	-0.23	-2.6	Sig.	-3.08	-1.29	Ns	-0.01
Wogeltena	0.66	Ns	1.84	3.19	Sig.	1.23	-0.79	Ns	-0.79	-0.41	Ns	0

Sig: Significance; Ns: Non significance; Q: Sen's slope; ZMK: Mann-Kendall z-value

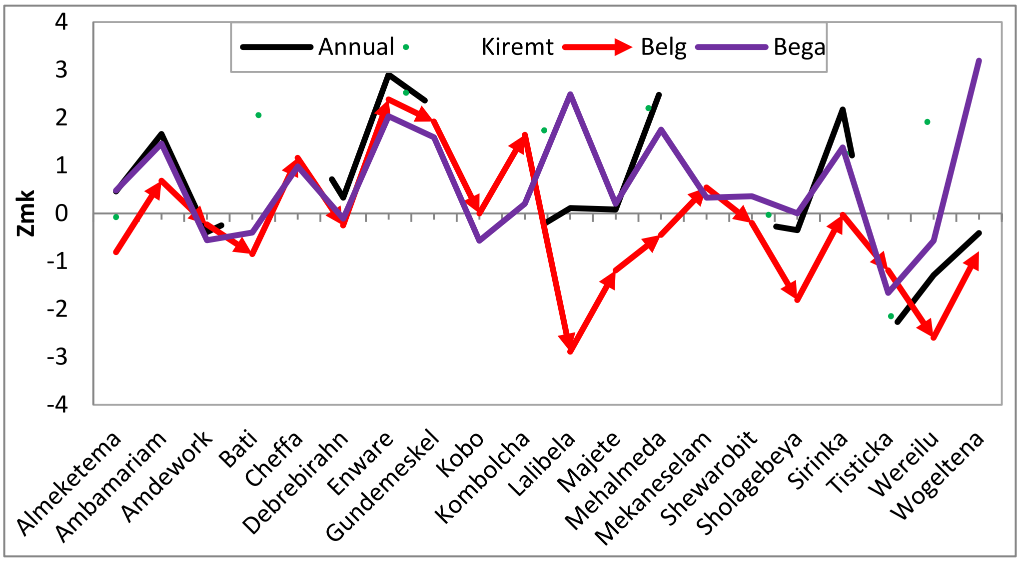

Figure 8: Rainfall trend (direction) over the study sites.

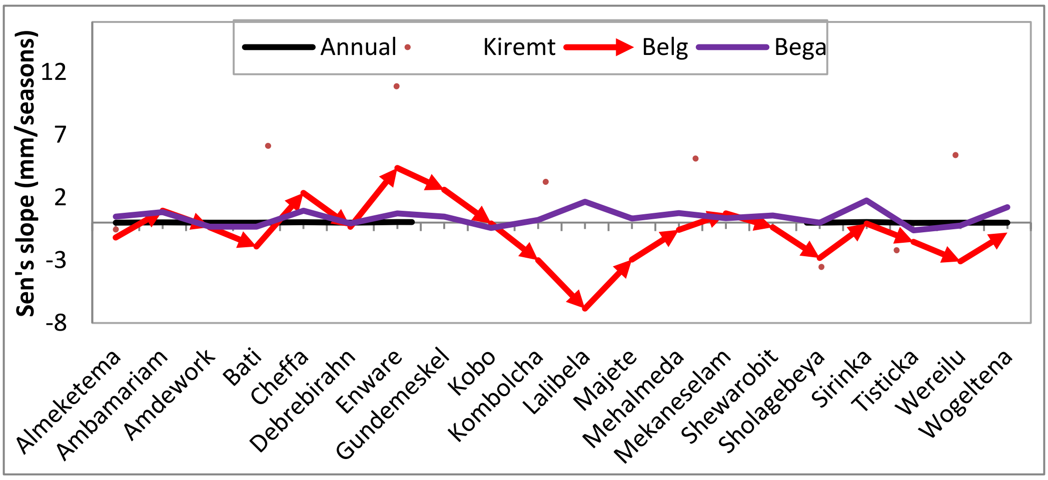

Figure 9: Cumulative rainfall change over the study sites.

slop estimator infers in what magnitude of rainfall are increased or decreased per seasons. In this study, both increasing and decreasing trends were observed in most study sites. Especially lalibela, Tisticka and Sholagebeya sites showed extreme decreasing trends during Belg season (Figure 8). On the other hand, the magnitudes of the rainfall were highly increased during the Kiremt seasons except Sholagebeya and Tisticka sites, while the extreme decline of rainfall was observed at Lalibela, and followed Sholagebeya and Wereilu sites during Belg season (Figure 9). On the same figure, the amount of Annual rainfall showed slight variations throughout the whole sites. Seleshi and Zanke reported that the decline of annual and Kiremt rainfall in eastern Ethiopia was observed since 1982 [11]. Similarly, Verdin confirmed the Seleshi and Zanke findings and reported that the annual rainfall become decline in Northeast Ethiopia since 1996 [12]. Verdin also reported the Kiremt rain has been consistent (i.e. no trends) in Ethiopia since the 1960s [12]. In contrast to Verdin, Conway (2000) reported that there are no recent trends in rainfall over the north eastern Ethiopian highlands [13]. Abegaz WB found that the rainfall trends showed decreasing during Belg, while increasing trends were observed during both Kiremt and Bega season at Dessie and Kombolcha meteorological sites in eastern Amhara [56]. However; Abegaz WB also concluded that there was no statistically significant trend in all rainfall seasons at Dessie and Kombolcha sites.

In general, the rainfall trend had a higher magnitude in the positive direction during Kiremt and Bega seasons, while higher variations were existed during Belg seasons at all sites (Figure 9).

The results of Pettitt's test are presented in Table 4. Some signal change points were observed in 1994, 1995, 1996, and 1997 for Annual, Bega, Belg, and Kiremt seasons, respectively. However, the change points have not reflected any shift at 5% significance level.

Table 4: Pettit's test for the seasonal time series.

Seasons	KT	P-value	Change points at	Shifting point	Significance
Annual	148	0.06	1994	No Shift	Uncorrelated series at 5% significance level
Kiremt	140	0.08	1997	No Shift	Uncorrelated series at 5% significance level
Bega	114	0.24	1995	No Shift	Uncorrelated series at 5% significance level
Belg	54	0.52	1996	No Shift	Uncorrelated series at 5% significance level

CONCLUSION

The overall results in all stations revealed a clear pattern of stationary, mean the stationary or independency was persisting in most lag times. The effects autocorrelation in all seasonal time scale were not visible. The Mann-Kendall test and Sen's slop revealed that an increasing and decreasing trend with a very smooth and slight magnitude were observed during the Annual season. On the other hand, the magnitudes of trends were found to be higher during Kiremt seasons. Any significant seasonal change points were not detected during all seasonal time scales. Although the significant autocorrelation was persisted at lag 1, it showed decreasing within the confidence interval throughout the time lags. One should notice the interpretation of the "significance" of the correlation at various lags need care because at least one approximate, out of total observations may happen correlations with a significant level. However, the need for testing the whole time series significance is mandatory to identify the effects of serial correlation in the time series data. The analysis results provide further knowledge to improve this time series data and understanding the direction of the climate and would be useful for future planning and management of agricultural practice in the study area.

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