Flow Indices Variability in Humid Subtropical of Upper Awash River Basin, Ethiopia

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Flow Indices Variability in Humid Subtropical of Upper Awash River Basin, Ethiopia

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Abstract

Investigating the hydrological extremes indices at high resolutions describing the whole stream spectrum is essential for the comprehensive assessment of watershed hydrology. The study focuses on a wide-ranging assessment of river discharge in annual mean, peak, and high and low percentiles flow at the Upper Awash River basin, Ethiopia. Statistical tests such as coefficient of variation, flood variability to characterize the flow regime and Tukey's test to detect decadal variability. Modified Mann-Kendall test, Sen's slope estimator, innovative trend analysis and Pettitt's test were applied to see trends, and change points in time series, respectively. Results showed that the basin was characterized by moderate to high variability. Spatially, main tributaries showed a higher variability, almost in all-time step and characterized by higher flood variability. The large discharge receiving rivers resulted in a moderate to high and lower discharge variability. Test statistics resulted in a positive increasing trend dominating most time scales at a 5% significant level and higher magnitude of slope trend in peak flow. A negative trends were also exhibited. Hombole main outlet site experienced decreasing trend in high percentile flow. In comparison, complete trend direction agreements were observed (except in few series). Flow indices showed an upward shift and downward shift mainly in the year 2000s and the significant decadal variation resulted in comparable with change points. The study provides an understanding of water resources variability, which will be necessary to apply operational water resources strategies and management to restrain the potential impacts of variability nature of the streamflow.

Key Words: Variability, Discharge, modified MK test, ITA

1 Introduction

Water resource management is a severe issue for sustaining the environment due to its variability. It is generally understood that the chain reaction of climate variability and land use land cover change impacted the hydrological cycle components (Legesse et al. 2003, 2010; Bao et al. 2019; Liu et al. 2020). In the first instance mainly, extreme hydrological events such as floods and droughts are of consequences (IPCC 2014). Climate change impact on streamflow is extensively studied. In particular, precipitation and temperature change are sensitive to change in streamflow characteristics (Hailemariam 1999; Jha et al. 2004; Guo et al. 2008; WaleWorqlul et al. 2018; Nilawar and Waikar 2019; Vandana et al. 2019) at basin and at global scale (Palmer et al. 2008). On the other hand, due to increased human-induced land cover change, such as noticeable urbanization, cropland expansion, deforestation, population growth, etc., the sub/terrestrial hydrological process have been affected (Nie et al. 2011; Billi et al. 2013; Shawul et al. 2019). Thus, climate change is not the only the causer of hydrological regime change. However, the discharge of the rivers is of significant implications in parts of extensively developed and center of socioeconomic undertakings for future water resources availability, water resource planning, and flood discharge management.

The topographic, climatic characteristics and recent anthropogenic activities have made the rivers vulnerable to varying discharges and Awash River basin is no exception to it. The river basin is the most exploited basin for agriculture (irrigation and rainfed agriculture) and the center of socioeconomic activities. The basin experienced frequent extreme hydrological (i.e., riverine floods and flash floods), and climatological hazards in the past 3 to 4 decades (Edossa et al. 2010; Belayneh et al. 2014). The dense population with urbanization in the region, water supply, irrigation, and hydroelectric dams, are dependent on the rivers originating in the upper land, including the capital city of Addis Ababa, and Adama town. In particular, the Upper basin has undergone an extensive land cover change (Shawul and Chakma 2019; Tadese et al. 2020b) over the past 3-4 decades and indicated the impacts on hydrological cycle variables (Shawul et al. 2019; Tadese et al. 2020a). However, extreme discharges in response to land cover change are more pronounced in small-scale watersheds (Blöschl et al. 2007; Apollonio et al. 2016).

In order to explore hydrological change and variation, identifying a trend and probable change point is a robust inference toward local climate change and anthropogenic activities (Gebremicael et al. 2017; Belihu et al. 2018). It is worth mentioning several factors that affect river flow discharge such as reservoir operation, water diversion, water withdrawal, irrigation scheme, implementation of flood control structures etc. With

global warming, intensification of hydrological cycle expected to continue into the future and directly manifests in a pronounced way in extreme hydrological conditions, i.e., flooding and water availability (Asadieh and Krakauer 2017; Tabari 2020). Moreover, observed extreme flow is considerably vital in water resource management and climate and anthropogenic activity assessments. Numerous hydroclimatic metrics are available in literature to detect trends in average, annual, monthly, seasonal, extreme (high and low) resolutions for better hydroclimatic insight in detail (Bekele et al. 2017; Gudmundsson et al. 2018; Ruwangika et al. 2020). Peak-over-threshold approaches is also alternative to annual maximum flow often associated with flood frequency analysis.

Several studies have been carried out in Ethiopia, focusing on hydroclimatic trends at catchment scale (Belihu et al. 2018; Orke and Li 2021) and basin scale (Tekleab et al. 2013; Jaweso et al. 2019). Hydroclimatic variability is the primary concern in the basin to water resource availability, especially in Awash River basin (Bekele et al. 2017; Taye et al. 2018; Daba and You 2020). Recent trend studies carried out by Gedefaw et al. (2018), Tadese et al. (2019) and Daba et al. (2020) used annual and seasonal time scale in the Upper Awash River basin hydrometric station. Daba et al. (2020) reported no trends in annual and seasonal (Kiremt and Belg) discharges and Bega season showed significant trends at two stations. They indicated increasing discharges were abundant in the Upper Awash basin. Tadese et al. (2019) applied trend test over Awash River basin annual and seasonal steps, and increasing trends were observed predominantly. Gedefaw et al. (2018) concluded a decreasing trend of annual discharge in Upper Awash River flow on the basis of the average flow of four stations. Although, at main river outlet, for instance, Hombole station conflicting trend results were reflected on the annual scale. These studies focused on detecting the homogeneity tests and trends in hydroclimatic variables using commonly MK test and Sen's slope estimator at courser time scales. Long-term hydroclimatic evaluation alone cannot be satisfactory in understanding the pattern characteristics of temporal variations and it is important to examine at different time scales. It has the advantage of defining the entire range of flows observed each year. Moreover, water managers are interested in flood and drought assessment in a basin like Awash River basin where surface flow availability depends on precipitation for rainfed and agricultural irrigation as the backbone of the economy and food security. In this case, though there have been studies on long-term streamflow variability in the river basin under investigation, and it could not describe the high-resolution variations. Investigating the hydrological extremes indices at high resolutions describing the whole stream spectrum is essential for the comprehensive assessment of watershed hydrology.

Several studies have been carried out using statistical test methodologies to measure the significant changes in time series. Parametric and non-parametric tests have been used to identify the presence of significant trends in hydroclimatological studies (Partal and Kahya 2006; Wilson et al. 2010; Jaiswal et al. 2015; Meresa et al. 2017; Drissia et al. 2019). Other recent trend analysis tools are based on time frequency, such as wavelet transformation (continuous and discrete wavelet transform), but the complex analyses (Ruwangika et al. 2020). Hydrological data are mostly not normally distributed. Compared to the parametric test (linear regression), the non-parametric test (Mann-Kendall, Sen's slope, Spearman rho test, etc.) has no prerequisite assumptions of distribution of the data series and is preferably robust to non-normally distributed data series and outliers. Many studies have widely used a rank based non-parametric Mann-Kendall (MK) test (Petrow and Merz 2009; Degefu et al. 2019; Jaweso et al. 2019) and Pettitt's test (Arrieta-Castro et al. 2020; Ryberg et al. 2020) for trend and change point detection in hydroclimatic data series, respectively. The MK test, however requires the serial independence of data time series. Innovative trend analysis (ITA) was developed by Şen (2012). In most recent ITA has been widely used to detect trends in annual and seasonal rainfall (Wu and Qian 2017; Caloiero et al. 2018; Gedefaw et al. 2018; Wang et al. 2020), monthly total precipitation (Ay and Kisi 2015), annual temperature (Gedefaw et al. 2018), pan evaporation (Kisi 2015), Solar radiation (Zhou et al. 2018) in different areas of the world. In hydrological variables, Kuriqi et al. (2020) applied MK test, Sen's slope estimator and ITA to assess trends in Godavari River basin of India for monthly, annual mean, annual maximum and minimum flow and seasonal time scales. ITA has been compared with MK, Sen's slope estimator, linear regression and Spearman's Rho test in all these studies. It is superior to detect sub-trends in data series from graph plots, independent of the statistical distribution and autocorrelation assumptions and sample size. MK test coupled with Sen's slope and ITA is demonstrated to be exceedingly effectual in detecting both quantitative and qualitative trend analyses.

Moreover, the evidence obtained from such analysis is vital in developing a compressive plan and mitigation approaches at basin scale. The long-term river discharge trend, especially the extreme hydrological events, are preconditions in the basin where flood results loss to the lives and crops. For this reason, it is needed to use a high resolution of stream data to detect trends in tributaries and main river sections to identify hydrological behaviour in the regions. Therefore, systematic evaluation of hydrological indices that capture the critical aspects such as decadal, mean annual, peak flow and flow percentiles yearly time step (99^{th}, 95^{th}, 90^{th}, 10^{th},5^{th}, and 1^{st}) indices of streamflow evident the understandings availability of water resources and sustainability of the ecosystem in river basin. Moreover, underlying the significant change detection of hydrological indices is

particularly important to understand the increasing concern of the collective effect of climate changes and human activities on hydrological responses. The result has more comprehensive practical application to integrated water resources management and adaptation measures. Hence, the study aims to investigate the discharge variability, detect significant trends, and change-point in long-term hydrological indices of the Upper Awash River basin.

2 Materials and Methods

2.1 Study Area and Data Sets

The study was conducted in Upper Awash River basin (UARB) bounded between $8^0$1' and $9^0$4' latitude and $37^0$58' and $39^0$4' longitude Fig. 1. The mean annual precipitation over the regions is 1030 mm (Daba et al. 2020) and higher (Mulugeta et al. 2019). Unimodal rainfall distribution (Edossa et al. 2010) and humid subtropical highland according to Köppen climate classification zones of Ethiopia. Awash basin is characterized by variable climate conditions resulting in frequent floods and droughts.

The Digital Elevation Model of the Awash basin ranges from 4195 to 240 masl (meter above sea level) and Upper Awash elevation covers above 1500 masl. The Awash River originates at the highland of Ethiopia Ginchi at an elevation between 2400 and 2900 masl in the Western and flows through high plateaux to north eastward. The study region is the strategic source of water resources. The majority of the population are living on the highland areas, above 1500 amsl. Due to the climatic condition, soil fertility, and suitability for agriculture, the regions are under intense pressure compared to others downstream. The upper highland areas are composed of high plateaux, high to mountainous relief hills, and dissected plateaux with hills plain. Rapid population increment and urbanization predominantly modified the land-use system in the upper basin.

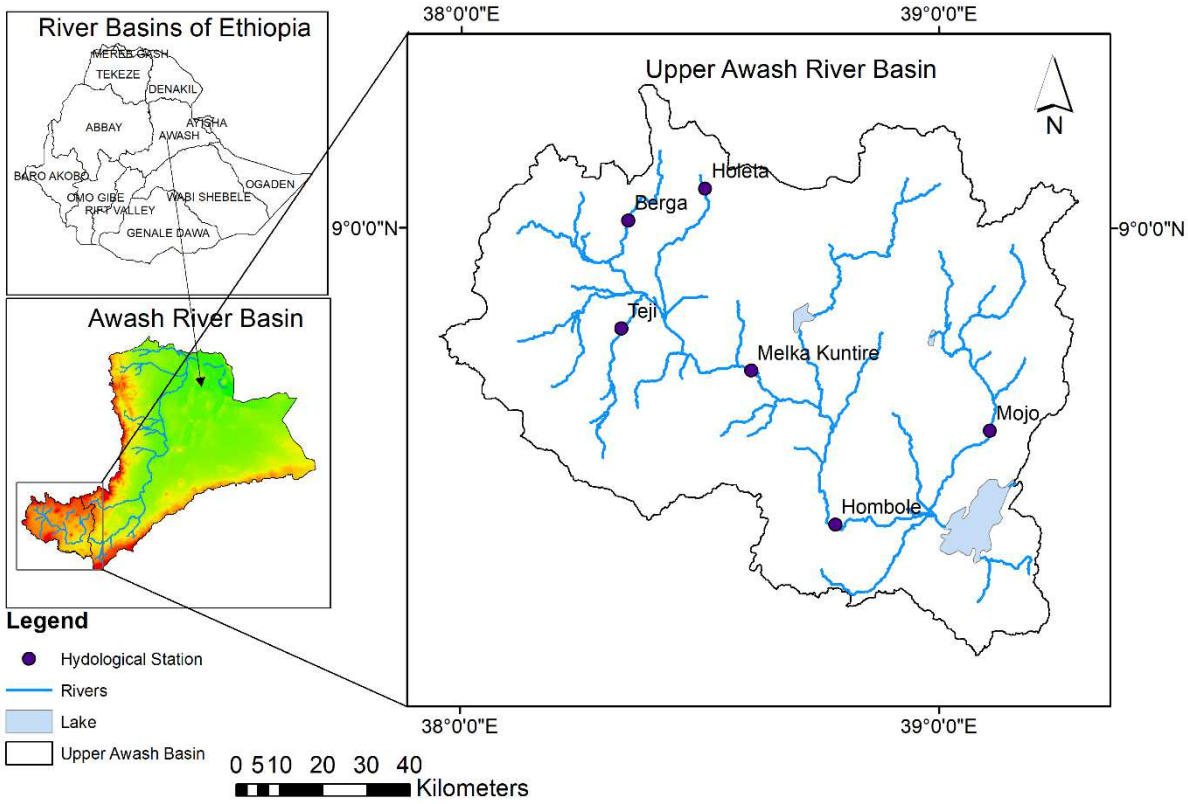


Fig. 1 River basin of Ethiopia, digital elevation model of Awash River Basin, UARB stream networks, lake, and hydrological stations

Long historical daily streamflow data were obtained from the hydrology department, Ethiopian Ministry of Water, Irrigation and Energy. Sets of representative gauging stations (Fig. 1), Holeta, Berga Teji, Melka Kunture, Hombole and Mojo are selected for the current study from upper to lower reach based on the data availability. Table 1 presents the catchment area of the stations, data sets of the diverse periods and the percentage of missing data series, which were filled later using linear regression techniques. The selected stations have a maximum of 48 years of observations and have at least 35 years. The spatial stations are clustered: upper reach includes four stations (Holeta, Berga, and Teji), middle consists of one station (Melka Kunture) and lower space include two stations (Hombole and Mojo).

Table 1 Data sets: list of stations, area, period of record and percentage of missing data

Stations	Area (km^2)	Period of record	Percentage of missing
Holeta	199	1975-2009	5.4
Berga	248	1975-2012	4.04
Teji	662.5	1980-2014	8.1
Melka Kunture	4456	1965-2012	1.77
Hombole	7656	1968-2014	0
Mojo	1264.4	1970-2014	5.2

The annual mean, annual peak flow, and percentiles flow of 99^{th}, 95^{th}, 90^{th} defined as the high flow and low flow as 10^{th},5^{th}, and 1^{st} were extracted for analysis from daily data series. Considering large sets of hydrological variables enables us to explore the broader impacts of the climate and anthropogenic on watershed hydrology.

2.2 Statistical Analysis

In order to provide the existence of healthy hydrological characteristics over the historical period, coefficient of variation and discharge variability index were used in this study to explore further variability in hydrological indices. The statistics of coefficient variation (CV) is the ratio of standard deviation to mean. This study employed coefficient of variance to summarize streamflow variation degree to mean streamflow record periods of annual mean, annual peak and percentile flows and determine the significant level of variation in the data structures. CV has been applied in the long term hydroclimatic variability studies (Chen et al. 2014; Kisaka et al. 2015). For the present study the fundamental statistics CV values were defined as normal (<0.2), moderate (0.2 - 0.3), and highly variable (> 0.3) to periods of records (Tadese et al. 2019). Flood discharge variability index (maximum discharge divided by the annual mean discharge, Q_{max}/Q_{mean}) were used in this study to characterize the hydrological regime characteristics in the watershed. The indices were demonstrated in river discharge behavior (Hansford et al. 2020) study over 575 gaging stations in response to different climatic zones, including the humid subtropical climate type.

In addition, Tukey's HSD (honestly significant difference) multiple comparison test was used to evaluate the pattern of difference between means. Before Tukey's HSD test, if the analysis of variance among the groups of means is significant, it means at least one group differs from the other groups, and detail can be referred from Williams and Abdi (2010). Tukey's test at a decadal resolution of the annual mean flow, peak flow, 95th and 10th percentile flows was applied to test the mean variability. The time interval was selected from 1970-1979, 1980-1989, 1990-1999, and 2000-2009. All pairwise differences were evaluated using the same sample size

used for the most significant difference. The null hypothesis assumed that there was no significant difference between means and the alternative hypothesis was assumed that a significant difference exists in means at a 5% significance level. The Tukey's HSD appraoch has been applied to test the hydrological variation in decedal resolution in Lake Tana Basin, Ethiopia (Tigabu et al. 2020).

2.3 Trend Analysis Methods

2.3.1 Mann-Kendall Trend Test (MK)

In the current study, a robust non-parametric MK trend test (Mann 1945a; Kendall 1975) method was applied to detect trends in the hydrological time series. MK test, however, requires the serial independence of data time series. The existence of serial correlation leads to the rejection of the null hypothesis (no trend) and accepts the significant trend (Von Storch and Navarra 1995). The procedure for MK tests starts with statistic (S), and is given by Eq. (1).

$$Sgn = \sum_{i=1}^{n-1} \sum_{j=i+1}^{n} Sgn(X_j - X_i) \tag{1}$$

Where $X_j$and X_i are consecutive observations data and n is the length of the data series. The $Sgn(X_j - X_i)$ is set as,

$$Sgn(X_j - X_i) = \begin{cases} +1 & X_j - X_i > 0 \\ 0 \ if & X_j - X_i = 0 \\ -1 & X_j - X_i < 0 \end{cases} \tag{2}$$

The data series variance $Var(S)$ was estimated by:

$$Var(S) = \frac{n(n-1)(2n+5) - \sum_{i=1}^{q} t_i(t_i-1)(2t_i+5)}{18} \tag{3}$$

Where, n is the length of observations, q is the number of pairs observation in data series, t_i is the number of pairs observations in series at the time i.

Finally, the standard Z statistics value was calculated by:

$$Z = \begin{cases} \dfrac{S-1}{\sqrt{Var(S)}} & S > 0 \\ 0 \quad if\ S = 0 \\ \dfrac{S+1}{\sqrt{Var(S)}} & S < 0 \end{cases} \tag{4}$$

194

195 The Z value determines the existence of increasing, decreasing, and no trend in time series. When Z value
196 is greater than zero, it indicates the increasing trend, and a negative value suggests decreasing trend. The critical
197 value at a two-tailed 1%, 5%, 10% significant level is ± 2.576, ± 1.96 and ± 1.645. In this study, 5% significant
198 level was used to detect the trend and a significant increase or decrease is accepted if the $Z > \pm\ 1.96$ (Diop et
199 al. 2017)

200 **2.3.2 Modified Mann-Kendall Trend Test (MMK)**

201 The existence of serial correlation leads to the rejection of the null hypothesis (no trend) and accepts the
202 significant trend (Von Storch and Navarra 1995). Mann-Kendall test (Mann 1945b; Kendall 1975) do not
203 consider the lag-1 autocorrelation in hydrological time series. Before test was performed, the Ljubg-Box serial
204 autocorrelation test (Ljung and Box 1978) was used to assess individual variables. For N, serially correlated
205 observations contain the same information as N*< N (lower than original series size). In the presence of positive
206 (negative) serial correlation, the variance (S) of MK test is fluctuating (increase or decrease). Thus for this study
207 modified Mann-Kendall test for serially correlated data using the Yue and Wang (2004) variance correction
208 approach was used to reduce the effect of serial correlation and the corrected variance S of MK test is given as;

$$V(S)_{cor.} = CF * V(S) \tag{5}$$

209 Where $V(S)_{cor.}$ is corrected variance, $V(S)$ is the original variance of sample and CF is correction
210 factor. Yue and Wang (2004) introduced the correction factor CF expressed as follow;

$$CF = 1 + 2\sum_{k=1}^{N-1}(1 - K/N)r_k \tag{6}$$

211 Where r_k is the lag-k serial correlation of the observed serial and N is the total length of the data series.
212 Variance correction approach has been used to correct the serial correlated hydrological series data by many
213 latest studies and detected the trend to corrected variance (Wang et al. 2015; Azam et al. 2018). The test was
214 applied for annual mean, peak and high and low percentile flows at lag-1 to detect trends in the flow indices.

2.3.3 Sen's Slope Estimator (SSE)

If a trend exists, the magnitude of linear trend slope in time series is estimated using a non-parametric approach (Theil, 1950 and Sen, 1968). Monotonic trend slope was calculated using:

$$\alpha_i = Median \frac{X_i - X_j}{i - j} \forall i \geq j \quad (7)$$

x_i andx_j are the data observation corresponding to time i and j. The median of $N = n(n-1)/2$ for α_i is Sen's estimator of the slope where n is the number of periods. The α_i is tested against the two-sided test at 5% significant level and the actual slope is estimated by a non-parametric test. The sign of the α_i obtains the increasing if α_i is positive and decreasing if α_i is negative.

2.3.4 Innovative Trend Analysis (ITA)

The ITA was first developed by (Şen 2012). The data time series is divided into two equal sub-series and ordered in ascending. The first half time-series sets are placed in the x-axis, and the second half time data sets are also placed in the y-axis in the Cartesian coordinate system. If the two sub-series are alike, the data points in the plot scatter show along the 1:1(45^0) line, which divides into upper and lower triangles. Upper exhibits an increasing trend if the data points fall above the 1:1 line and if the data points found in the lower triangle, the series reveals decreasing trend and no trend along the 1:1 line (Şen 2012). Else, the scatter point present non-monotonic trend consisting of different trends in the time series categorized into cluster as low, medium and high cluster points. The ITA trend slope (S) is estimated by using the following expression (Şen 2017).

$$S = \frac{2(\bar{X}_j - \bar{X}_i)}{n} \quad (8)$$

Where $\bar{X}_i$ and $\bar{X}_j$ are the arithmetic average of the first and second half time series, respectively, and n is the data set length. The stochastic property of S is a function of the arithmetic mean of the first half and second half time series. As $\bar{X}_i$ and $\bar{X}_j$ are also stochastic variables, the first-moment order (expectations) of the slope trend can be obtained by taking the expectation of both sides:

$$E(S) = \frac{2}{n}\left[E(\bar{X}_j) - E(\bar{X}_i)\right] \quad (9)$$

In case of no trend detection, the centroid point fall on the 1:1 line (45^0), indicating that $E(\bar{X}_i) = E(\bar{X}_j)$ and hence, $E(S) = 0$. Then again, the variance of the slope can be computed as $\sigma_s^2 = E(S^2) - E^2(S)$, which is

equal to the second-order moment of the slope variable. Since $E(\bar{X}_i^{\,2}) = E(\bar{X}_j^{\,2})$, then the variance of slope equation can be expressed as;

$$\sigma_S^{\,2} = \frac{8}{n^2}\left[E(\bar{X}_j^2) - E(\bar{X}_j \bar{X}_i)\right] \tag{10}$$

The correlation coefficient of the two mean values in the stochastic process is expressed:

$$\rho_{\bar{X}_j \bar{X}_i} = \frac{E(\bar{X}_j \bar{X}_i) - E(\bar{X}_j)E(\bar{X}_i)}{\sigma_{\bar{X}_j \bar{X}_i}} \tag{11}$$

Substituting the correlation coefficient of the two mean numerator into Eq. (11) and considering $\sigma_{\bar{X}_j} = \sigma_{\bar{X}_i} = \sigma/\sqrt{n}$ gives the variance of the slope as follow:

$$\sigma_S^{\,2} = \frac{8}{n^2}\frac{\sigma^2}{n}(1 - \rho_{\bar{X}_j \bar{X}_i}) \tag{12}$$

Where, $\rho_{\bar{X}_j \bar{X}_i}$ is the correlation coefficient of the two mean values in the stochastic process, finally the standard deviation of the slope is given:

$$\sigma_S = \frac{2\sqrt{2}}{n\sqrt{2}}\sigma\sqrt{1 - \rho_{\bar{X}_j \bar{X}_i}} \tag{13}$$

Therefore, the statistical significance of the innovative trend slope test can be achieved through a normal (Gaussian) PDF with zero mean and standard deviation equal to σ_S. If at α percent significance level, the confidence limits of a standard normal PDF with zero mean and the standard deviation is S_{cri}, then the confidence limits (CL) of the trend slope is obtained as:

$$CL_{(1-\alpha)} = 0 \pm S_{Cri}\sigma_S \tag{14}$$

Where α denotes significance level and σ_S is the standard deviation of the slope. The null hypothesis, H_0, infers that there is not a significant trend if the calculated slope value, S, remains less than a critical value, S_{cri}. Otherwise, an alternative hypothesis, H_a, is accepted when $S > S_{cri}$. In this study, 5% significance level was used for the ITA approach to mean annual, peak, high and low percentile flows.

2.4 Change-point Analysis

A non-parametric Pettitt's test (Pettitt 1979) was used to detect the abrupt change in the middle of the data series. This test was chosen because it is free distribution testing, adaptation of the rank-based Mann-Whitney test and has the advantage of sensitivity to identify the exact time of step change is anonymous. The method was most widely used in hydrological and climatological data (Kundzewicz and Robson 2004; Jaweso et al. 2019; Daba et al. 2020). If the observed sequence $X_1, X_2, X_3 \ldots Xn$ has a change point at time t such that $X_1, X_2, X_3 \ldots Xt$ has distribution function $f_1(x)$ which is different from the distribution function $f_2(x)$ of the series $Xt+1, Xt+2, Xt+3 \ldots, Xt+n$. Then the non-parametric test statistics,

$$K_T = Max\left|U_{t,T}\right|, 1 \le t \le T \tag{15}$$

Where $U_{t,T} = \sum_{i=1}^{t} \sum_{j=i+1}^{T} \operatorname{sgn}(X_i - X_j)$, sgn(x) = 1 if X > 0, 0 if X = 0, and -1 if X< 0. The confidence level p, of the sample n length and its associated K statistics,

$$\rho = \exp\left(\frac{-K}{n^2 + n^3}\right) \tag{16}$$

In this study, the 5 % significance level was considered. The null hypothesis of change not exist is rejected if the p values is less the specified significance level ($\alpha = 0.05$) and accept the alternative hypothesis, change exist in the data series. The constancy statistical properties (stationary) of the stream flow indices before and after change point was evaluated by plotting probability of exceedence against descending order of stream flow of two group (before and after) using Weibull plotting position (Rao and Hamed 2000), $i/n + 1$, where i is rank in ascending order and n is the number of observations. Probability of exceedence of 10%, 50% and 90% was chosen to compare the discharge both before and after change point.

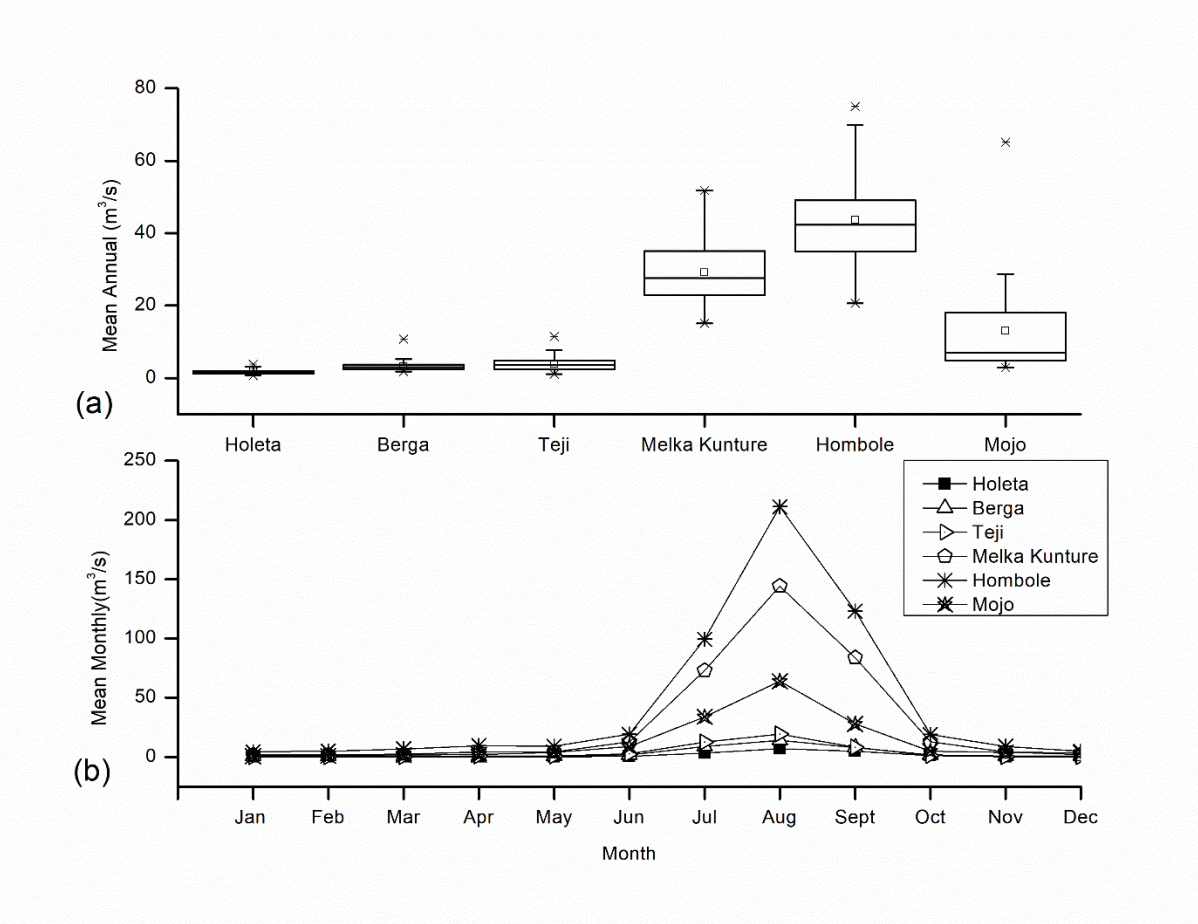
3 Results and Discussion

3.1.1 Spatial Variability of River Discharge

The highest mean annual discharge value was found to be in the lower reach of Hombole (43.66 m^3/s) and the least in the upper Holeta (1.62 m^3/s) hydrometric station. River discharges were confined to Kiremt (JJAS) and receive maximum precipitation in Kiremt season, but significant variation in runoff discharges could be

280 associated with catchments area and geomorphology. For instance, Hombole has the largest (7,656 km^2) and
281 Holeta (119 km^2) has the smallest catchment area. The annual daily peak flow exhibited a high in the middle
282 station of Melka Kunture (944.125 m^3/s) in August and a lower reach of Hombole (803.10 m^3/s). The daily
283 discharge of Hombole and Melka Kunture stations had above zero minimum values while other stations had
284 zero. The upper headwater station showed a maximum release of 45.95 m^3/s at Holeta.

285 Main tributaries have shown almost the same mean annual flow in upper reach and the middle with lower.
286 Stations along with the main river discharge accumulation are significantly increasing from Melka Kunture
287 toward Hombole station. Spatially, the lower reach has the most extended duration and highest flow availability
288 cover. On the other hand, stations in the middle and lower reach received higher average streamflow than upper
289 reach. Compared to the other stations, the temporal flow distribution indicates that Hombole receives the highest
290 flow annually. Middle reach obtained higher records as well. Holeta was the least to receive flow on annual
291 scale. The flow in October may be attributed to the lesser flow difference between small rain and dry season in
292 most stations, including Melka Kunture in middle and Hombole in lower. The most increased average monthly
293 flow was presented in August, while July and September were moderate, and June and October lowest mean
294 values during Kiremt (Fig. 2b). In addition, there was no significant dissimilarity in mean in all stations between
295 October and June. Thus, the observed discharge value corresponds with the highest and tiny rainfall season.
296 Over all spatial patterns of mean annual and mean monthly discharges are similar.



297

298 **Fig. 2** Long-term mean annual (a) and Monthly river discharges (b) of each station in UARB

299 The streamflow variability in mean annual flow, peak flow and percentiles flow was defined by the
300 coefficient of variation (CV) statistics and is given in Table 2 and Table 3. Almost 66.6% of the station have
301 shown high (> 0.3) variability in mean annual and peak flow series, respectively. Remarkably, as far flood is
302 the concerned in the tributaries, the peak flow time series in tributaries were found to have high variability
303 dominates in the region followed by moderate. Stations at main river also depicted high variability. It can be
304 seen that the CV value of the two river is almost similar in the mean annual and high percentile flow series,
305 which might be a reflection of spatial correlation. CV values are calculated for all stations in high and low flow
306 percentile, and almost all of the stations showed high variability and few of them are moderate. About 83.33%
307 of stations showed high variability in minimum flow (10^{th}, 5^{th} and 1^{st}), and all stations in the 99^{th} percentile were
308 found high variability. The two stations (Melka Kunture and Hombole) at the main river course showed
309 moderate variability in high flow (95^{th} and 90%). Conversely, main tributaries showed high variability in low
310 flow and high flow. The number of time series exhibited high variability, mainly in tributaries are substantially
311 high. In general, about 50% of the stations in mean annual, 66.6% of the stations in yearly peak flow and 50%

of the stations in high and low flow showed above the averaged CV in respective time step, thus flows indices experienced high variability.

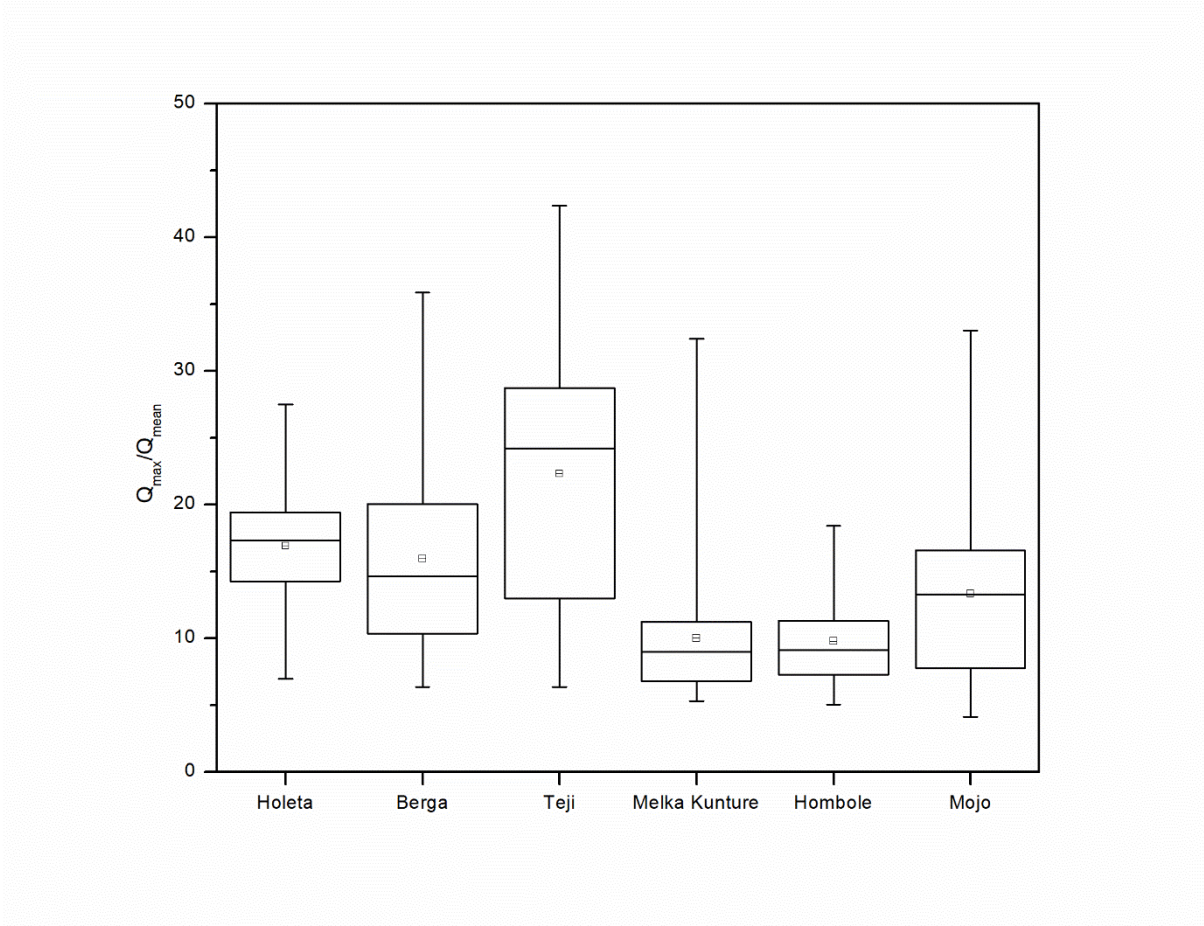
Table 2 Mean annual, seasonal, peak flow (m^3/s), and CV of each station at different time scales

Station	Mean Annual	CV	Mean Peak	CV
Holeta	1.62	0.41	28.29	0.28
Berga	3.21	0.47	51.16	0.47
Teji	3.93	0.52	87.63	0.43
Melka Kunture	29.14	0.28	291.82	0.48
Hombole	43.66	0.27	426.91	0.33
Mojo	11.91	0.77	209.78	0.51
Average		**0.45**		**0.42**

Table 3 Mean high and low percentile flows (m^3/s), and CV of each station at different time scales

Station	Mean 99th	CV	Mean 95th	CV	Mean 90th	CV	Mean 10th	CV	Mean 5th	CV	Mean 1st	CV
Holeta	16.10	0.45	7.73	0.77	4.47	0.67	0.18	1.07	0.16	1.20	0.14	1.40
Berga	26.56	0.38	13.78	0.36	9.32	0.41	0.26	1.59	0.23	1.67	0.20	1.82
Teji	43.98	0.53	16.21	0.60	9.76	0.75	0.12	0.93	0.09	0.94	0.08	1.00
Melka Kunture	188.29	0.32	138.32	0.27	111.16	0.29	1.02	0.36	0.77	0.37	0.57	0.38
Hombole	303.38	0.32	206.49	0.29	153.22	0.30	3.34	0.26	2.93	0.27	2.56	0.29
Mojo	114.67	0.66	70.67	0.90	53.49	1.07	0.22	0.53	0.18	0.63	0.14	0.64
Average		**0.44**		**0.53**		**0.58**		**0.79**		**0.85**		**0.92**

The Flood regime characteristics, the ratio of annual maximum streamflow to mean annual flow (Q_{max}/Q_{mean}), was calculated for the individual station and shown in Fig. 3, highlighting the division of flood magnitude. Thus, one station (Teji) had a significant ratio in the basin. Except at Hombole, the ratio of other stations has also resulted in greater than 20. On an average, the ratio was highest at Teji (22.30) upper station and lowest at Hombole station (5.0) of the lower station. The highest frequent flood variability was recorded recently at Teji station between 2005 and 2014. It was noted that the regression coefficient ($R^2 = 0.10$) exhibited a positive relationship, implying area size has an insignificant influence on flood variability. Main tributaries stations depicted a higher magnitude of flood regime characteristics, while large flow receiving rivers showed lesser (<10).



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329 **Fig. 3** Box-plot of flood variability ranges in terms of maximum, minimum and mean for each station

330 ### 3.1.2 Inter Decadal Variability

331 The river discharge changes were evaluated at decadal resolution considering annual mean, peak, 95th and 10th
332 percentile flows series (1970-2009) are representative data sets. Moreover, the data sets were checked against
333 variance of the group mean difference is significant. Using Tukey's test, decadal mean flow variability exhibited
334 that three stations of the different resolution had a significant difference in mean at $\alpha = 0.05$. The mean annual
335 discharge of Melka Kunture between the 1980s and 2000s depicted a significant increase and the mean
336 difference between the two decades was significantly different (Fig. 4a). The mean variation between the 1970s
337 and 1980s, 1970s and 1990s, 1970s and 2000s, 1980s and 1990s, and 1990s and 2000s were insignificant. In
338 95th percentile flow, the mean significant increase from the 1980s to the 2000s was exhibited (Fig. 4c). In the
339 case of Mojo station, the decadal mean annual flow (except for the 1970s and 2000s) variation was significant
340 (Fig. 4b). The flow was significantly increased between the 1970s and 1990s and insignificantly decreased from
341 the 1990s to 2000s. The 1990s mean annual flow was highly significant compared to the 1970s (Fig. 4b). In
342 peak flow, decadal mean variation was a significant increase between the 1970s and 1990s and a significant

decrease 1990s and 2000s (Fig. 4d). The highly significant mean difference was shown between the 1970s and 1990s. The peak flow of the rest decades did not show significant variation. The 95% percentile flow for Mojo indicated a significant increase from the 1970s to the 1990s and a significant decrease between the 1990s and 2000s (Fig. 4f). It is, therefore, apparent mean decadal variations exist between periods.

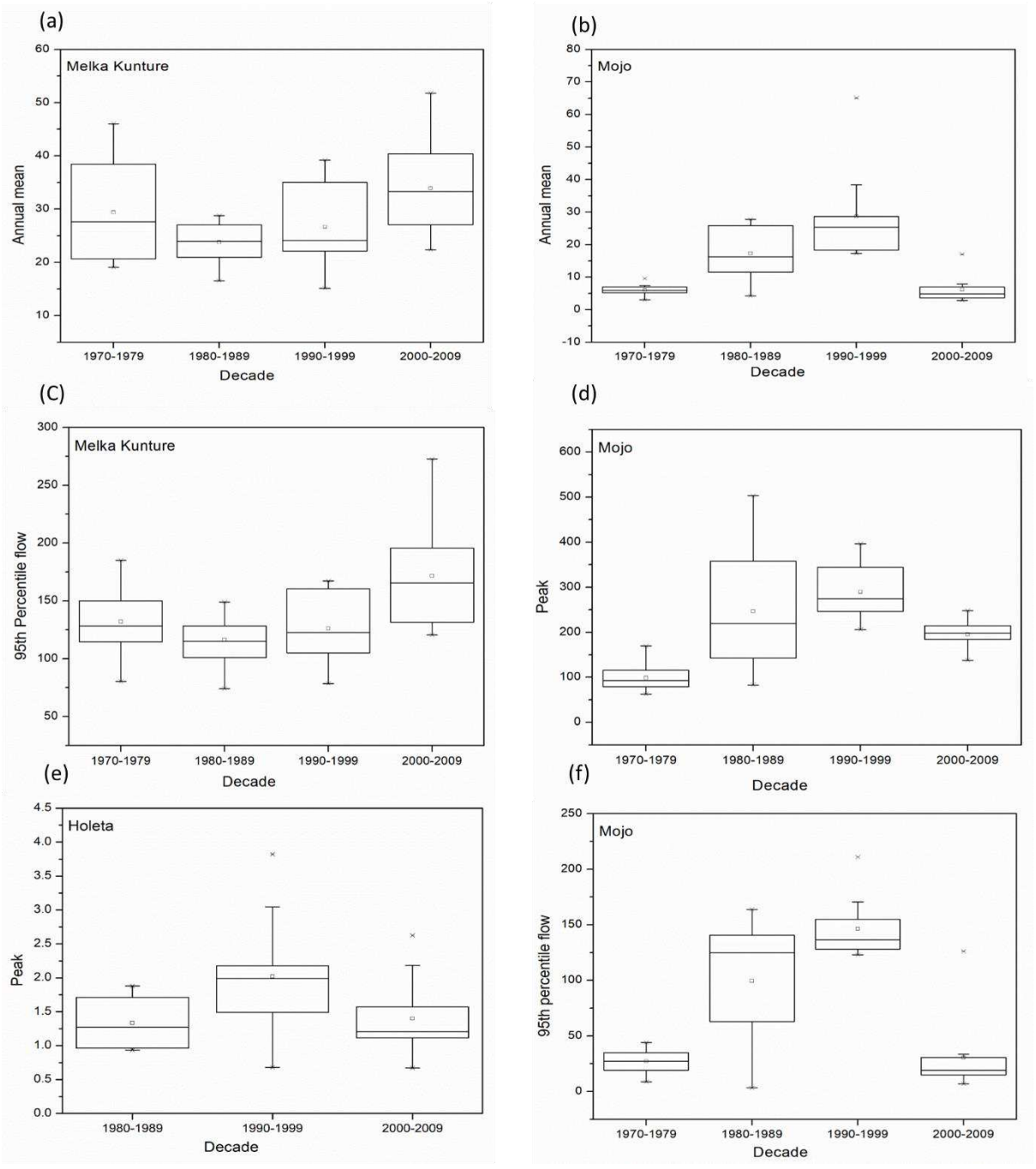

Fig. 4 Decadal variability in different flow indices of various sites of UARB

For Holeta peak flow, the mean variations between the 1980s and 2000s was insignificant, but between the 1980s and 1990s, and 1990s and 2000s, a significant increase and significant decrease was revealed, respectively

(Fig. 4e). Thus, significant mean variation presents between the 1980s and 1990s and 1990s and 2000s. Spatially, Mojo has shown a higher difference in mean peak flow. It can be seen that the 1990s flow has shown an increasing trend compared to the 1980s and a significant decrease in the 2000s in Mojo and Holeta (except Melka Kunture).

Similar observations were found in Lake Tana basin rivers in Ethiopia (Tigabu et al. 2020). The higher degree of anomaly flows in these stations are driven by land use, land cover change and climate change. For instance, Shawul et al. (2019) demonstrated that the urbanization and cropland expansions (1974-1984 and 2000-2014) triggered the variation of surface runoff in Upper Awash river basin (including the Melka Kunture and Mojo subbasin). In a similar study in the neighbour basin, the expansion of cultivated land and urban areas has also significantly increased the surface runoff in Andassa watershed, Blue Nile basin (Gashaw et al. 2018).

3.1.3 Trend Analysis

A lag one serial correlation coefficient indicates 20 data series of 48 total data series was auto-correlated significantly in the annual mean, peak flow, and percentiles flow. Thus, considering the serial correlation being in these time series, a variance correction procedure (Yue and Wang 2004) is crucial before performing trend analysis to diminish the defects that define the trend in the original MK test. Based on this, the trend results were discussed in the subsequent sections.

3.1.4 Trends in Mean Annual flow

Table 4 presents the summary results of temporal trends by modified MK trend and magnitude of the trends by Sen's slope in mean annual, peak, high and low percentile flow time step at 5% significance level ($Z_{critical}$ = 1.96). The Z statistics of mean annual was evident that a mixture of positive and negative trends, indicate increasing and decreasing trends. In most stations, the mean annual series showed that increasing trend but statistically not significant. MMK statistics exhibited decreasing trend (Holeta and Mojo) and an increasing trend (Berga,Teji, Melka Kunture and Hombole). The magnitude of decreasing and increasing trend rates using the Sen's slope were also provided in Table 4. The least trend magnitude was observed in mean annual flow time series.

Table 4 Value of Z of the Modified Mann-Kendal test (MMK) and Sen's Slope Estimator (SSE) for mean annual, peak flow, high and low percentile flows

Flow indices	Test	Holeta	Berga	Teji	Melka Kunture	Hombole	Mojo
Mean Annual	MMK(Z)	-0.790	1.613	1.199	1.34#	0.606	-0.987#
	SSE	-0.009	0.023	0.023	0.112	0.040	-0.043
Peak	MMK(Z)	-0.160#	2.118*	3.65*	1.592#	-1.881	1.662#
	SSE	-0.016	0.230	1.534	1.795	-1.098	2.086
99th	MMK(Z)	-2.00*#	0.559	2.563*	1.5#	-1.524	-0.456#
	SSE	-0.111	0.039	0.757	0.872	-0.558	-0.234
95th	MMK(Z)	-3.51*	0.669	0.678	1.61#	-0.884	-0.941#
	SSE	-0.093	0.028	0.038	0.554	-0.247	-0.359
90th	MMK(Z)	-5.316*	0.618	-2.243*	1.827	-0.434	-0.566#
	SSE	-0.064	0.016	-0.073	0.604	-0.079	-0.105
10th	MMK(Z)	-5.76*	3.316*#	-5.25*#	0.678	1.626#	2.869*
	SSE	-0.060	0.011	-0.004	0.000	0.011	0.003
5th	MMK(Z)	0.243	3.460*#	-4.758*#	-0.203	1.723#	2.031*
	SSE	0.000	0.009	-0.004	0.000	0.013	0.002
1st	MMK(Z)	-0.585	3.315*#	-5.157*#	1.544	4.312*#	2.446*
	SSE	0.001	0.008	-0.004	0.001	0.021	0.002

*and # represent significant trend at 5% significance level, and serially correlated series, respectively.

At all stations, MMK statistics result agreed in sign with the result of SSE at 5% significance level. The result indicated that most of the stations in tributaries were characterized by increasing trends and higher trend magnitude in main river section.

The trend of mean annual detected by ITA was presented in Table 5. The result showed that slope S of mean annual flow was dominated by positive values and almost all of them were significant at 95% confidence level. ITA plots illustration of mean annual was shown in Fig. 4. For instance, the ITA for Berga station in mean annual flow, most of the points fall above the 1:1 line indicating increasing trend, further confirms the trend statistics slope S. It has been noted that MMK trend statistics of mean annual flow at Teji and Mojo showed the opposite sign with ITA approach. These signs were also reflected in slope statistics. The spatial patterns of mean annual showed that significant trends were detected almost in all stations. Therefore most of the stations are characterized by significant trends at 5% significance level. Gedefaw et al. (2018) remarked average ITA measured decreasing trends for four annual Awash River discharge stations. However, Hombole and Holeta stations disagreed with the observation for the study period from 1980-2016. These stations have different trends in the time series and direct that the higher point, the stronger the direction.

Table 5 ITA test results of mean annual and Peak flow in six stations

Stations	Slope S	Slope Standard Deviation	lower CL at 5% Sign. Level	Upper CL at 5% Sign. Level
		Mean Annual		
Holeta	-0.008*	0.0024	-0.0048	0.0048
Berga	0.041*	0.0085	-0.0166	0.0166
Teji	-0.006	0.0121	-0.0237	0.0237
Melka Kunture	0.134*	0.0117	-0.0229	0.0229
Hombole	0.056*	0.0224	-0.0438	0.0438
Mojo	0.045*	0.0416	-0.0815	0.0815
		Peak		
Holeta	-0.044	0.0236	-0.0463	0.0463
Berga	0.327*	0.0435	-0.0852	0.0852
Teji	1.323*	0.0877	-0.1718	0.1718
Melka Kunture	2.748*	0.3516	-0.6892	0.6892
Hombole	-0.891*	0.3118	-0.6111	0.6111
Mojo	1.720*	0.2075	-0.4066	0.4066

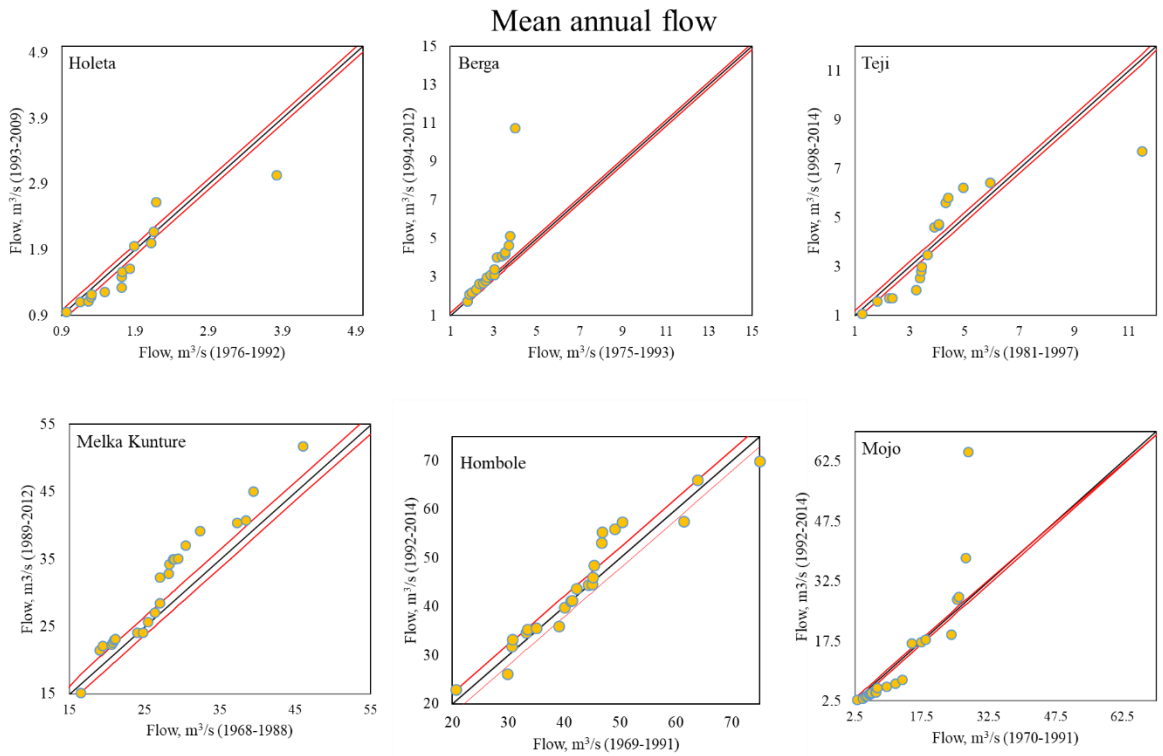

Fig. 5 ITA plot results in mean annual flow of each station in UARB

3.1.5 Trends in Peak Flow

The temporal peak flow trends detected by MMK test and trends magnitude by SSE were presented in Table 4. In peak flow time series, most of the stations exhibited increasing trends (except Holeta and Hombole); however, Significant increasing trends was observed in Teji station (1.53 $m^3/s\ year^{-1}$) and Berga (0.23 $m^3/s\ year^{-1}$). The decreasing rate of 1.09 $m^3/s\ year^{-1}$at 95% confidence level was exhibited at the outlet of Hombole station. The spatial pattern of trend magnitude at Mojo station, the increasing rate is as high as 2.086 $m^3/s\ year^{-1}$, followed by Melka Kunture at rate of 1.79 $m^3/s\ year^{-1}$.

Peak flow trend test using ITA method was given in Table 5. The result showed that two negative and four positive values, but all of them were significant (except at Holeta). The spatial pattern of significant trend from upper toward lower river reach, ITA graphical illustration of four increasing stations (Berga, Teji, Melka Kunture, and Mojo) and two decreasing stations (Holeta and Hombole) are given in Fig. 5. The ITA plot for peak flow shows that most points fall above and below 1:1 line signifying the trend obtained by slope S statistic. Peak flow at Berga and Mojo exhibits two different trends in the time series. Then it is possible to see points in different regions, for example, lower and upper regions. These indicate non-monotonic trends exist in the time series. The upper region (low flow) points are high in number, which shows that the stronger the trend.

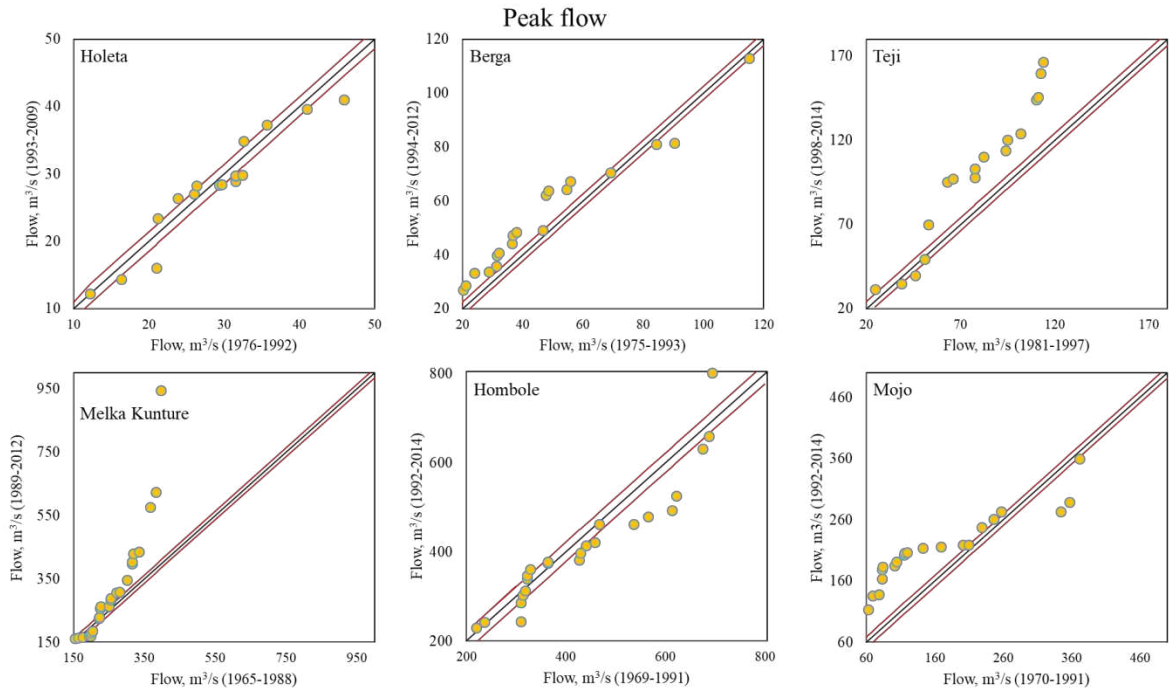

Fig. 6 ITA plot results in peak flow for each station in UARB

3.1.6 Trends in High and Low Percentiles Flows

Stream flow series such as high and low flows are of significant objectives in planning and establishing annual water balance, in addition to managements of dam's projects (Diop et al. 2017; Sahoo and Jha 2020). The high and low flow percentile trends identified by MMK and trend magnitudes by SSE was also summarized in Table 4. Most stations in the high flow categories (99^{th}, 95^{th} and 90^{th}) exhibit decreasing trends, while low flow (10^{th},5^{th} and 1^{st}) distribution showed increasing trends at 5% significance level. The high percentile flow of two tributaries (Teji and Berga) and Melka Kunture identified as increasing but at the out let point showed a decreasing trends. Of these, Low percentile flow at Berga, Teji and Mojo exhibited a significant trend, but a very week rate of change per year. Three stations (Berga, Hombole and Mojo) showed a positive significant trend in low flow. The rate of variation in all stations was revealed much less than unity.

The ITA result for high and low flow percentile was presented in Table 6. The slope S of all stations was obtained and almost all of them were significant at 5% significant level. The high percentile flows were dominated by negative slope s and significant trends. Spatially, Hombole and Holeta showed significant downtrend in upper percentile flow. Positive slope S values were found for most of the stations in low percentile flow and all of them were significant. ITA plots in Fig. further confirm the positive slope S values in these stations, in which most of the points fall above the 1:1 line. However, composition trends were also observed in some stations (Teji, Hombole and Mojo) in high flow percentiles.

Table 6 ITA test results of percentile flow (90^{th}, 95^{th}, 90^{th} and 10^{th}, 5^{th} and 1^{st}) in six stations

99^{th} percentile flow

Stations	Slope S	Slope Standard Deviation	Lower CL at 5% Sign. Level	Upper CL at 5% Sign. Level
Holeta	-0.173*	0.017	-0.033	0.033
Berga	0.192*	0.017	-0.034	0.034
Teji	0.542*	0.050	-0.098	0.098
Melka Kunture	1.346*	0.121	-0.237	0.237
Hombole	-0.038*	0.084	-0.164	0.164
Mojo	-0.230*	0.061	-0.120	0.120
		95th percentile flow		
Holeta	-0.141*	0.011	-0.021	0.021
Berga	0.100*	0.022	-0.043	0.043
Teji	-0.119	0.063	-0.124	0.124
Melka Kunture	0.707*	0.075	-0.146	0.146
Hombole	-0.038	0.084	-0.164	0.164
Mojo	-0.249*	0.099	-0.194	0.194
		90th percentile flow		
Holeta	-0.087*	0.015	-0.029	0.029
Berga	0.056*	0.021	-0.041	0.041
Teji	-0.202*	0.063	-0.123	0.123
Melka Kunture	0.600*	0.036	-0.070	0.070
Hombole	-0.018	0.088	-0.172	0.172
Mojo	0.171	0.113	-0.221	0.221
		10th percentile flow		
Holeta	-0.076*	0.013	-0.025	0.025
Berga	0.017*	0.001	-0.001	0.001
Teji	-0.005*	0.001	-0.001	0.001
Melka Kunture	0.005*	0.000	-0.001	0.001
Hombole	0.009*	0.001	-0.002	0.002
Mojo	0.002*	0.001	-0.001	0.001
		5th percentile flow		
Holeta	0.005*	0.002	-0.003	0.003
Berga	0.017*	0.001	-0.001	0.001
Teji	-0.005*	0.000	-0.001	0.001
Melka Kunture	0.002*	0.001	-0.001	0.001
Hombole	0.010*	0.002	-0.004	0.004
Mojo	0.002*	0.000	-0.001	0.001

444 * denotes the significant trend at 5% significance level

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448 Continued

	1st percentile flow			
Stations	Slope S	Slope Standard Deviation	Lower CL at 5% Sign. Level	Upper CL at 5% Sign. Level
Holeta	0.004*	0.002	-0.003	0.003
Berga	0.015*	0.001	-0.002	0.002
Teji	0.004*	0.000	-0.001	0.001
Melka Kunture	0.005*	0.000	-0.001	0.001
Hombole	0.017*	0.001	-0.003	0.003
Mojo	0.003*	0.000	0.000	0.000

449

450 *Represent significant trend at 5% significance level.

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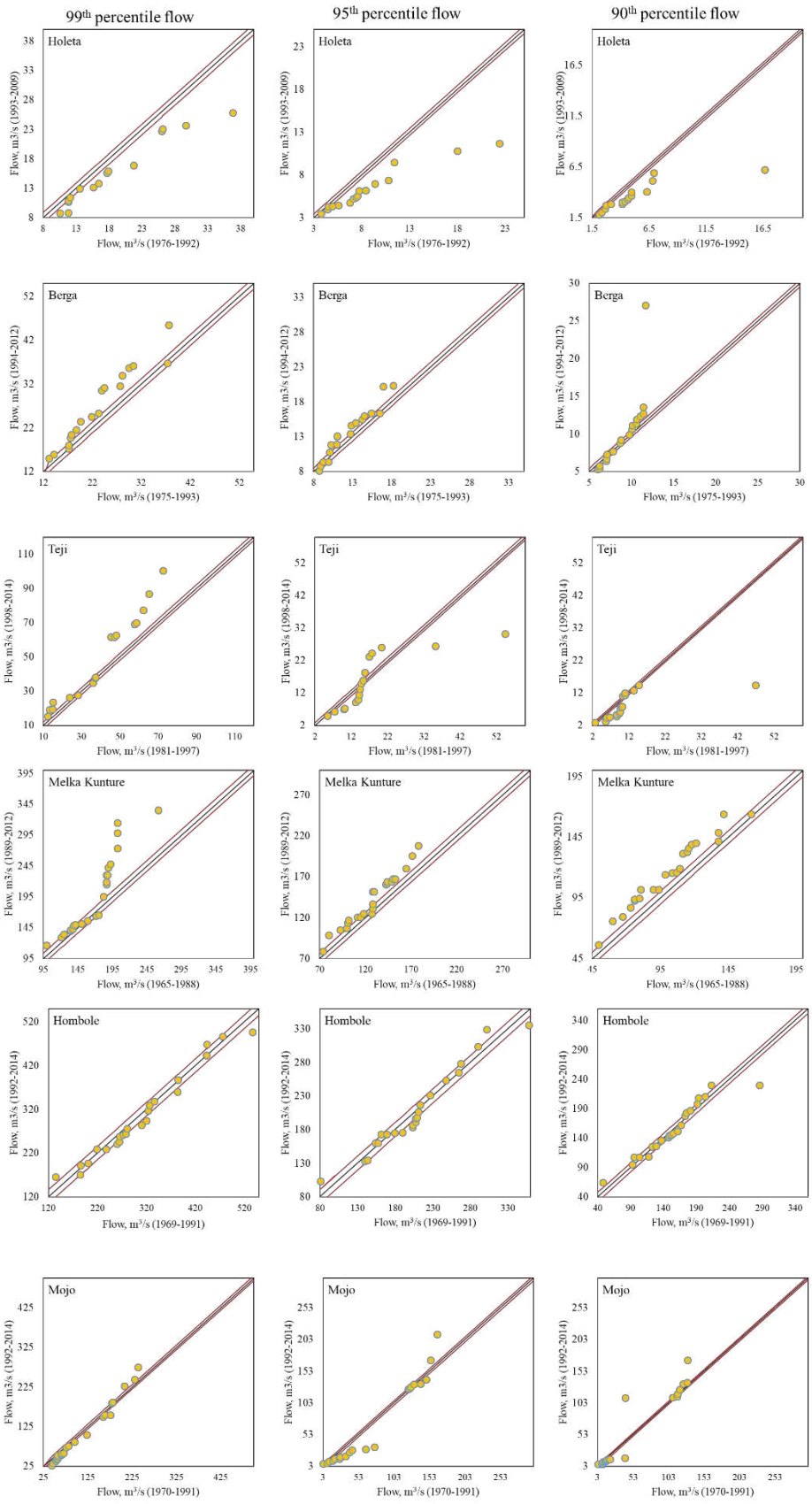

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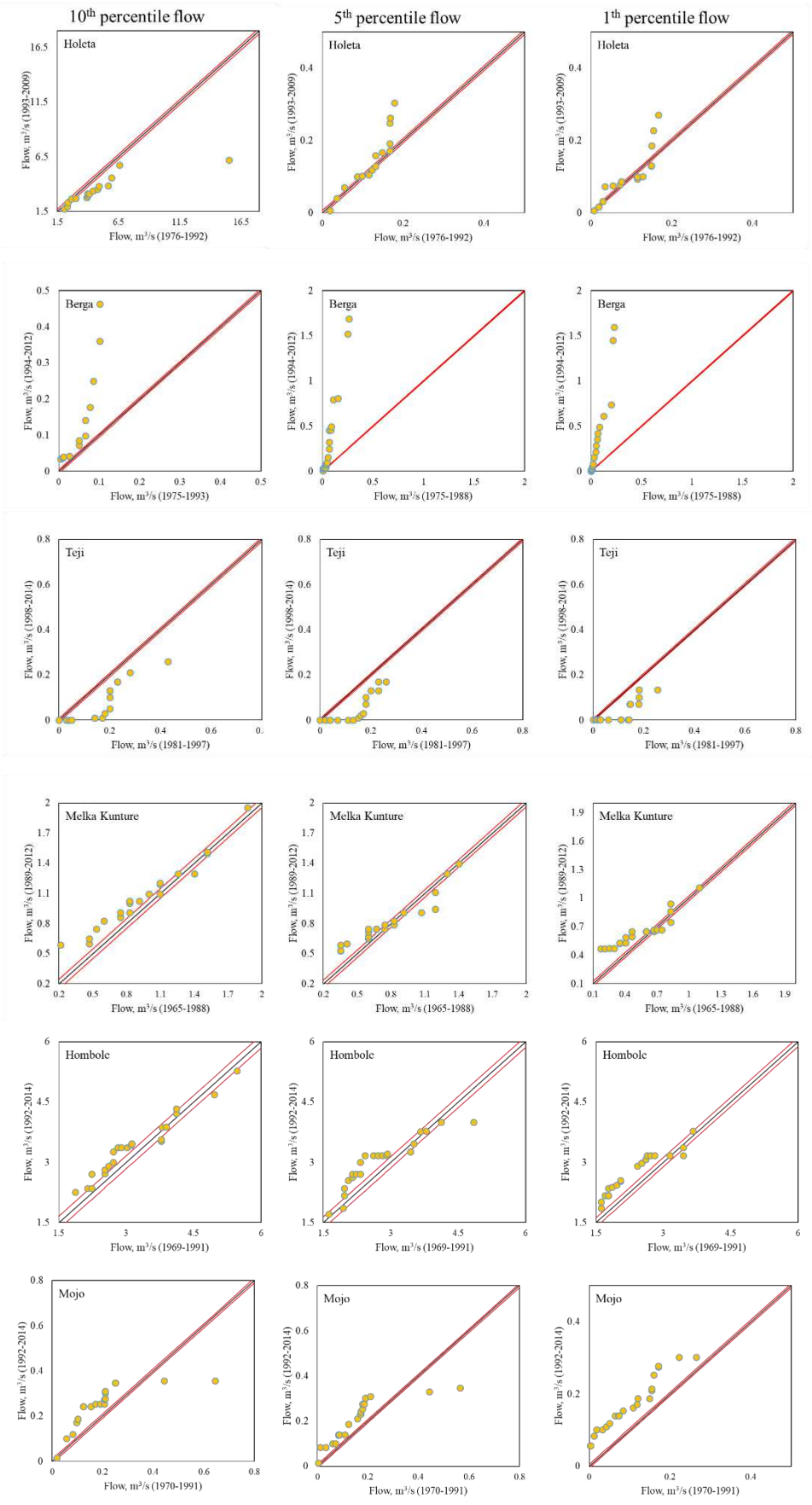
453 **Fig. 7** ITA plot results of 99th, 95th and 90th flow percentile at each station in UARB



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455 **Fig. 8** ITA plot results of 10th, 5th and 1st flow percentile at each station in UARB.

Generally the amount of flow at the outlet of Hombole site and Mojo station is decreasing and this can influence the hydropower production from the downstream Koka dam and increase the water stress. The trend direction of similar stations reported by Tadese et al. (2019) and Daba et al. (2020) showed complete agreement in annual scale. In the contrary, Gedefaw et al. (2018a) showed seemingly valid results, decreasing for Hombole, increasing for Holeta, and a significant increase for Berga in annual discharge flow for 1980-2016 at 5 and 10% significance level using MK and Sen's slope. Thus, the inconsistent result might be due to the start date of data used for these studies.

The decrease of flow across the basin station might be assoctiated with rainfall variability, for instance Holeta station (Tadese et al. 2019) and Hombole (Daba et al. 2020) and water usage for small irrigation activities in the basin. Despite the reduction of forest and grass land (increase built up area and cropland) from 1973-2006 in Holeta-Berga watershed (Gelet et al. 2010) and annual rainfall in Addis Alem (Daba et al. 2020)(near to Berga), the hydrological variables in Berga station showed an increasing trend. In addition another possible reason to increase the surface runoff was evidenced as land use land cover change in Melka Kunture and Mojo catchment (Shawul et al. 2019; Zena et al. 2020). Jaweso et al. (2019) indicated that the decrease in rainfall and increase in temperature consequence negative stream flow trends in the neighboring river basin of Omo Ghibe, Ethiopia. In other basin, same climatic characteristics, Tekleab et al. (2013) noted varied stream flow trends in the Abay/Upper Blue Nile basin, Ethiopia and indicated human activities and nature caused the variations. In addition, Assefa and Moges (2018) found a decreasing trend in low flow in 12 station of the 15 station in Blue Nile basin, Ethiopia. Land cover change and climate change were claimed responsible resulting in increasing runoff and evapotranspiration (increasing temperature thereby increasing evaporation from the soil and decreasing soil water) respectively. Further, Degefu et al. (2019) inspected spatial trends of 10 streamflow indices using the MK test and Sen's slope estimator at 57 hydrological stations for the highlands of Ethiopia. They found a significant increase in mean annual, seasonal (dry and wet), maximum and minimum flow (Qmax/min1day, Qmax/min7day, Qmax/min30day) variables and significant decrease trends in Qmin80p at 5 and 10% significant level. The result is consistent with other basin studies based on the same methodologies.

3.1.7 Trend Change-point Analysis

Abrupt changes may be attributed to natural or anthropogenic changes in climatic, hydrological or landscape process (Ryberg et al. 2020). In this study, the Pettitt test was carried out to investigate change point in annual mean, peak and high and low flow percentile flows considering a 95% confidence level. The change test result

was summarized in the Table 7 for stations that showed significant changes in the time series. The change point of peak flow for selected stations is displayed in Fig 9. Change points were detected in about 41.6% of the 48 investigated flow series and upward change was dominant. Most stations have unveiled a significant change point in the 2000s, very recently. From the decadal variation analysis in Fig. 4, the change point agrees with the mean shift in the 2000s. The significant change point for low percentile flows of Berga station was seen after 2004. For Teji station, the annual mean, peak and 99th percentile flow series breaks upward after 2005. In the contrary, in the same station, the significant downward change point in low percentile flows was indicated around 1994 and 1995.

Table 7 Table Pettitt test change point summary in a year (p-value < 0.05)

	Station	Berga	Teji	Melka Kunture	Hombole	Mojo
Time series	Annual mean	-	2005	2003	-	2000
	Peak	-	2005	2005	-	1983
	99th	-	2005	2003	-	2000
	95th	-	-	2003	-	2001
	90th	-	-	-	-	2000
	10th	2004	1995	-	-	-
	5th	2004	1994	-	-	-
	1st	2004	1994	-	2005	1990

At the outlet of Hombole station, the low percentile flow (1st percentile flow) showed a significant upward change in 2005. The second main river Melka Kunture station, exhibited an upward shift in 2003 and 2005 in annual mean, high flow percentile and peak flow series, respectively. Mojo station was the highest number of break points showed in the time series i.e. in 1983, 1990, 2000 and 2001. This had been reflected in decadal variation analysis in Fig. 4 (d). It increased in peak flow and low flow percentile (1st percentile flow). Further, inter decadal variation analysis confirmed the findings of the change point analysis.

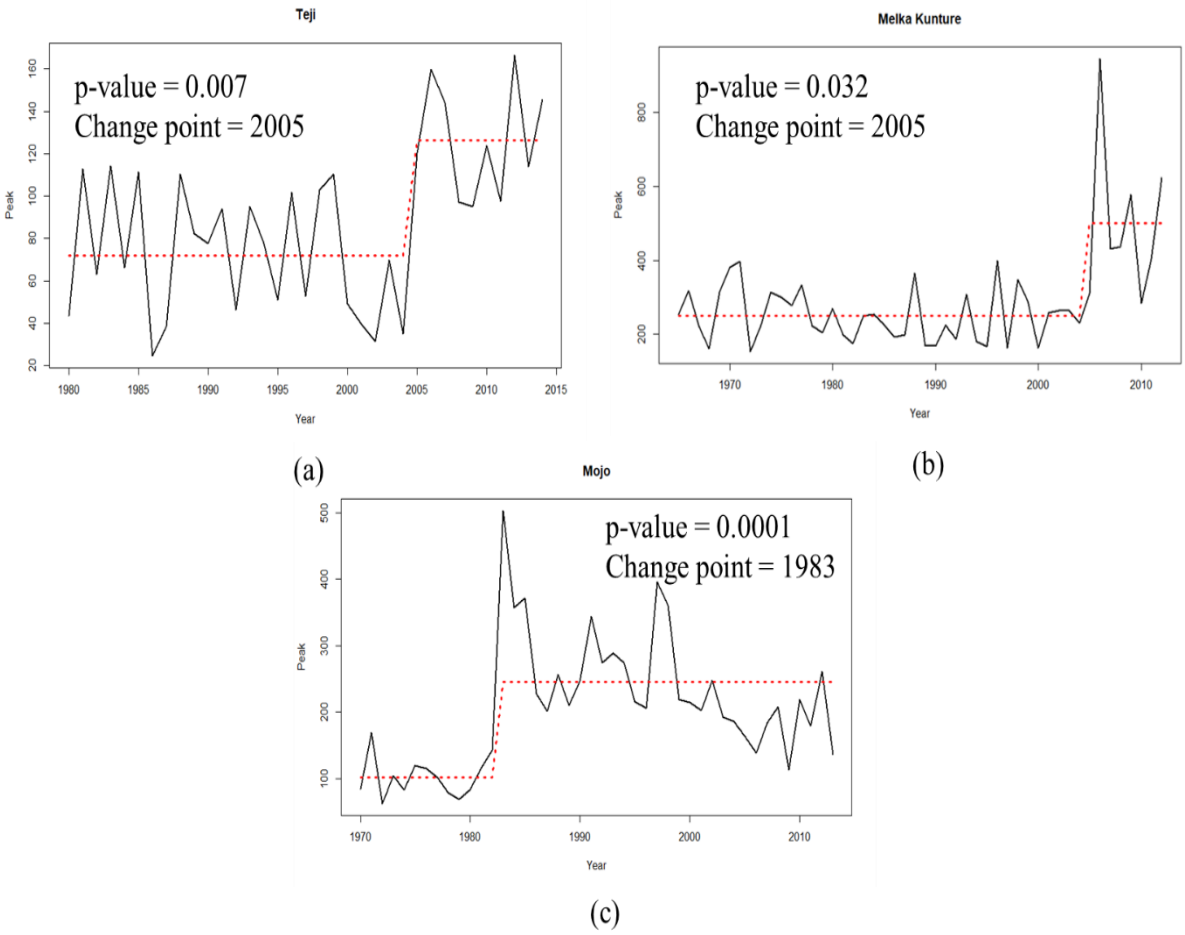
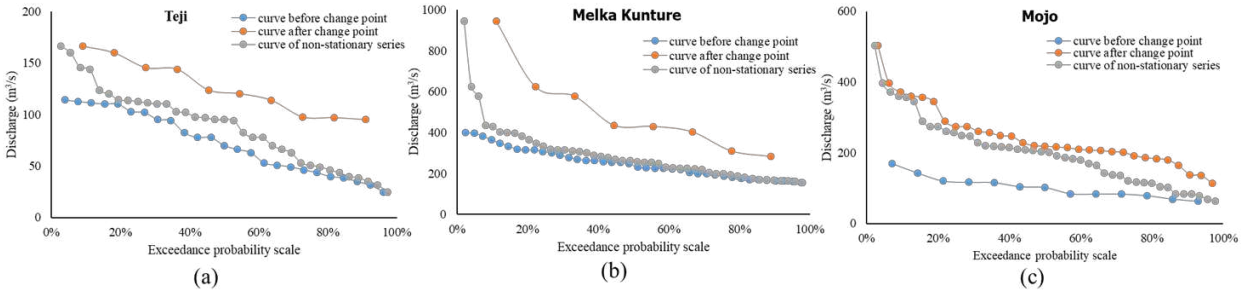


Fig. 9 Pettitt test result of peak flow stations a) Teji b) Melka Kunture c) Mojo

It is noted that the point change in Teji and Melka Kunture in annual mean, peak flow and high percentile flows has occurred at almost the same time, indicating the change in branch station also has an effect on the succeeding river station. The two tributaries Teji and Mojo resulted in a significant upward change in peak flow at different periods.

The hydrological series exhibited trends and change points, which are indicative of the nonstationary properties of the hydrological indices. The shape of the probability of exceedence curves before and after a breakpoint, and the nonstationary series of the peak flow was shown in Fig. 9. The magnitude of the peak flow exceeded or equaled to the specified exceeded probability scales are obtained for comparison before and after the change point. In Fig. 9, the exceedence probability curve demonstrated that the peak flow after the change point was found upward. For instance, for Teji station, the flood magnitude equaled or exceeded 10%, 50%, 90% of the time increased by 53.75, 52.14, and 62.66 m^3/s, respectively. The highest magnitude of change was seen in Melka Kunture followed by Mojo after the change point for the specified exceedence probability. Thus,

515 the peak floods after the change point were more significant than the peak flow before the change point equaled
516 or exceeded 10%, 50% and 90%.



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518 **Fig. 10** The exceedence probability curve for non-stationary series and series before and after change point: (a)
519 Teji (b) Melka Kunture (c) Mojo

520 The results are similar to the estimated trend analysis to flow series in the basin. Zena et al. (2020) reported
521 that similar significant change point (in the 2000 year) of the annual mean flow dropped by 80% at Mojo station
522 for the period of 1980-2015. During the Bega season (no rain with little flow), the change point was also
523 indicated in 1992, which is almost not far from the low flow to our finding (1990) but opposite direction. In
524 addition, the authors dictated that climate variability in the watershed has no connection with the decrement of
525 surface flow. The comparable changing pattern in a nearby basin, for instance, the mean yearly flow, detected
526 an upward shift in two major rivers around the late 1990s, the Upper Omo Ghibe basin of Ethiopia (Jaweso et
527 al. 2019). Upward and downwards change points exhibited in different catchments of Abay/Upper Blue Nile
528 basin, Ethiopia for 1/7-day annual minimum/maximum flows mostly in 2000s and 1980s (Tekleab et al. 2013).
529 The previous study in the Upper Tekeze–Atbara River basin, Ethiopia, Gebremicael et al. (2017) indicated
530 decreased low flow (1-day annual minimum flow) after around 2000 and high flow (1-day maximum yearly)
531 increased after 1995. In sum, this significant increment in peak flow in the tributaries, mainly upstream,
532 exacerbates the continuing flooding during the heavy rain periods (July and August). Thus, the increasing human
533 activities impact flooding and water availability in the future should be the primary concern, principally seasonal
534 peak flow and requisite land-use management intervention in the basin.

535 ### 3.1.8 Comparison of modified MK trend test and ITA

536 For the 12 mean annual and peak flow series evaluated by the MMK test and ITA method at 5% significant
537 level, significant trends were observed in 2 series by MMK test and 8 series by ITA method. ITA also detected

all significant trends identified by MMK test. The two trend analysis approaches revealed that 2 series in annual mean were inconsistent with the sign of the trend (opposite each other). It was also noted such difference by two methods in hydroclimatic trend assessment (Belihu et al. 2018). It is noted that there was complete agreement in directions between the trend tests, 8 increasing and 4 decreasing trends (including significant) by ITA and 8 increasing trends (including significant) and 4 decreasing trends by MMK test method. Also, the ITA method detected significant trends in mean annual and peak flow series that the MMK test has not identified. The trends statistics in the 36 high and low flow percentile series by MMK and ITA show that significant trends/directions were detected in 16 series by MMK and 32 series by ITA method, including the significant trends identified by MMK test. The 4 series in the high and low flow percentile showed disagreement with the trend sign. In sum, the closing agreement is observed between the MMK and ITA, 20 increasing and 16 decreasing trends were identified by MMK and 23 increasing and 13 decreasing trends were also seen by ITA including significant trend. In these tests, significant trends in time series that are not recognized by the MMK test are successfully spotted by ITA tests. ITA approached revealed more significant trends in the time series (increasing and decreasing trends) and included all significant trends identified by MMK.

In the present study, the agreement among the signs of the trends is observed but is not entirely consistent with significant trends. ITA method proved the ability to graphically show the non-monotonic trends in the same time series or hidden trends compared to the MMK test, helping to examine the flow properties in groups. It is rational to use ITA method to scrutinize the sub-trend in hydrological series rationally. In the case of this study, it was seen that the high flow region shows a substantial increase and decrease. As far as the flood is concerned in the region, the significant increase of high group in peak flow of the Melka Kunture station was observed. The present study performed a very different look from classical trend analysis for high-resolution hydrological data series. The classical MK and Sen's slope give overall trends directions and do not provide sub-trends graphically and respective quantitative estimation. Thus, ITA delivers clear insight into the temporal variability of hydrological series and is crucial to identifying the flow cluster that is increasing or decreasing for effective management of extreme hydrologic events in the basin.

In summary, it is essential to note that discharge variability varies spatially in terms of mean annual, peak, and percentiles flow under the investigated stations. Almost all of the stations in tributaries (upper, middle and lower reach) of UARB showed moderate to high variability (CV) in mean annual and peak flow, respectively. High variability was detected in tributaries (upper, middle and lower reach) in high and low percentile flow. The

567 main rivers (Melka Kunture and Hombole) showed moderate to high variability in most stations and were
568 dominated by moderate variability. The result demonstrated a very close coefficient of variation values to mean
569 annual, as Tadese et al. (2019) stated. The above discussions were consistent with (Billi et al. 2014) reported
570 that the annual runoff shows a broader range of variation among rivers in Ethiopia. Dettinger and Diaz (2000)
571 note the average year-to-year CV of streamflow across the globe is 0.49. The flood variability behaviour in
572 tributaries was found to be higher than in the main river. The high variability in low flow percentiles in tributaries
573 results in water deficiency for agricultural irrigation activities over the UARB. The decadal variation of
574 hydrological series exhibited a significant difference in mean in mean annual, peak and 95^{th} percentile flow and
575 was found to be related with detected change points.

576 In the past years, in different regions of the world, a non-parametric approach was used to evaluate the
577 hydrological series (Arrieta-Castro et al. 2020; Sahoo and Jha 2020). Spatial hydrological variability studies at
578 various scales have been indicated as very important for effective water resources management and planning for
579 present and future demands (Kuriqi et al. 2020) in the basin. In this study, the trend of eight flow indices were
580 evaluated by using the modified MK test (variance corrected based) and ITA at 5% significant level. It was
581 noted that there was complete agreement in directions between the trend tests, and ITA detected all significant
582 trends identified by MMK test. Spatially, increasing trends in mean annual and peak flow were dominant in
583 tributaries. The decreasing trends were noticed in high percentile flow at Homoble outlet and its adjacent Mojo
584 River, but oppositely the low percentile flows were increased. The low percentile flow in the tributaries was
585 shown a significant increase in Berga and a decrease (no trend magnitude) in Teji and Holeta. The Pettitt test
586 detected a significant change point in the 2000s, mostly an upward direction and the peak flow point out that
587 most stations in tributaries, including the main river Melka Kunture detected an upward change.

588 In support of the present study, several studies have analysed trends in flow indices in other parts of the
589 world and point out the possible drivers. The possible shift or trend change in record data over time is mostly
590 associated with the remarkably changing environment, global and local climate variability and land-use
591 dynamics (Wagesho et al. 2012) and nature (Arrieta-Castro et al. 2020). Sahoo and Jha (2020) indicated low
592 flow affected by the land cover change and water storage structures. In the present context, UARB, the potential
593 cause for streamflow change in the majority of subbasin might be linked to rainfall distribution and land cover
594 change. Other possible factors, such as antecedent soil moisture (Wasko and Nathan 2019) in the basin can be
595 attributed to an increase or decrease in discharge flows.

596 The study of streamflow characteristics in planning and developmental activities such as hydropower,
597 irrigation, water supply projects, drought and flood, its impacts on operational and efficient functioning are
598 imperative. In hydroclimatological time series observation, the recent human activities and climate variation are
599 two major determinant factors that invalidate the stationary assumption in hydrological studies (Milly et al.
600 2008). Thus, hydrological studies, water resource planning and management to account the adjusting land cover
601 land use and climate change in the basin. Therefore, in agreement with this study, it was seen that the UARB
602 streamflow trend and change matches with previous studies in and around the region. This study examined the
603 spatial characteristics of temporal trends and change in peak, high and low flow percentiles time series in high
604 resolution. The spatiotemporal depth analysis of river discharge provides insight into better water resources and
605 flood management in the basin. Thus, the detail information of flow characteristics can be described using higher
606 resolution than the courser (e.g. seasonal flow evaluation).

607 **4 Conclusions**

608 The study aimed to investigate hydrological variability, trend and change in hydrological indices of the UARB.
609 Statistical tests such as coefficient of variation were used to explore the variability, flood variability to
610 characterize the flood regime and Tukey's test to evaluate decadal mean variation. The modified MK test, SSE
611 and recent ITA were also applied to detect trends and Pettiitt's test to identify probable change time in
612 hydrological time series in different time steps, annual mean, annual peak, and upper and lower percentile scale
613 at 5% significance level. Based on the assessment attempted, the spatial flow indices variability, trend and
614 change over the basin were concluded as follow:

615 Rivers discharge varies spatially from the lower amount in the upper to higher in the lower reach. The
616 interannual coefficient of variation of UARB was portrayed as moderate to high variability in discharge series
617 and most of them exhibited high variability. Flood regime characteristics were found higher in main tributaries
618 than the main river, implying high discharge variability in branches. The spatial pattern of the variability in
619 tributaries was exhibited as high. Tukey's multiple mean difference comparison technique was applied and few
620 stations series showed significant differences between the mean of groups. Significance increase and decrease
621 in mean difference between the mean of groups was noted and enabled to confirm the change point, for instance,
622 in the 2000s.

The serial correlation test identified most of the station time series were serially correlated. Based on the assessment, a modified Mk test based on the variance correction techniques was utilized to reduce the effect of autocorrelation. The modified MK test and ITA, and SSE revealed increasing trends were dominant, followed by decreasing tends in the basin at 5% significant level in the all-time series considered in the study. Significant decreases and increases were identified in low percentile flow in tributaries. The higher magnitude of increase was revealed in the branch river in peak flow series at Mojo station. Notably, it was noted that there was an agreement between the two trend analysis approaches in terms of positive and negative statistics values. In some series, the opposite sign of trends was identified. The two trend analysis methods were able to signify the temporal hydrological variability over the basin, but the ITA method can detect the sub-trends than the modified MK test and does not require a serial correlation test in time series. Based on these assessments, the discharge variability in all-time steps in tributaries was dominated by positive trends, including Melka Kunture (the main river). Overall at the outlet point of Hombole site, flow indices experienced a negative trend in peak and high percentile flow compared to the annual mean and low percentile flow, which shows a positive trend.

Using Pettitt's test, change point analysis revealed that the annual mean, peak flow, and high percentile flow commonly exhibited significant probable shift points in the 2000s and low percentile flow in the 1990s. Most station's time series showed a significant upward shift (except Teji low percentile flow). Climate variability, land cover change, water withdrawal for agricultural irrigation are possible mechanisms responsible for changes in streamflow indices.

Higher resolutions of diverse data scales are essential to remark the difference in the spatiotemporal variability of river discharge and able to detect in depth variation. The flow variability reflects the causes and probability of flood and drought in the tributaries. Integrated water resources management is necessitated to overcome the water resources management aspects and flow control severely limits variability in the tributary. The study provides an understanding of water resources variability in depth, which will be necessary to apply operational water resources strategies and management to restrain the potential impacts.

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Authors' contributions

Sintayehu Yadete Tola: conceptualized, methodology, analyze study data, results and discussion and conclusions. Amba Shetty: supervised the study and edited the manuscript. All authors read and approved the manuscript.

Availability of data and material

All data generated or analysed during this study are included in this article.

Code Availability

Not applicable.

Declarations

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Consent to Participate

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Conflict interest

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