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Changing Characteristics of Regional and Site-based Frequency Distribution Under the Non-Stationary Process

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ABSTRACT

The probability of the occurrence belonging to heavy rainfalls that directly triggers the flood is estimated with the common assumption that the process by which it occurred is under stationary conditions. By accepting this threat as if it does not exist in our globe, which is faced with the reality of global warming and climate change, estimating the required design values in the construction of hydraulic structures with frequency analysis of the relevant data would cause the failure of the water-related structures. This study was carried out to come up with how the regional and site-based frequency distribution would change under non-stationary conditions. The L-moments algorithm, Monte Carlo Simulation technique, and the magnitude of the trend calculated by Innovative Trend Analysis (ITA) were involved in scrutinizing the impact of non-stationary conditions on frequency analysis of annual maximum daily rainfall data sets. By including the own time-dependent change (trend) of each data in synthetic data, synthetically produced rainfall data was intended to reflect the actual conditions effectively. The simulated data has increased the heterogeneity of the entire region compared to the observed data and led to considerable differences in regional and site-based quantile estimates, and this difference became a nonlinear increase, especially after the 90% probability level. Based on this study, by considering stations with longer and equal or nearly equal observation periods in alternative regions, the change of frequency distribution behaviour in non-stationary conditions can be scrutinized with different methodologies.

1. Introduction

Increasing attention on global warming arising as a result of anthropogenic activities has resulted from its impacts ravaging the natural functioning of the ecosystem. The Intergovernmental Panel on Climate Change (IPCC) (2013) reported that heavy rainfall events have increased in a quantitative sense towards the end of the 20th century. Hirabayashi and Kanae (2009) pointed out that more than 300 million people could be affected by even minor floods in the years between 2060 and 2070. Feyen et al. (2008) foresaw that in European countries, the economic losses resulted from the flood in the next century would rise to € 18 billion from € 6.5 billion levels. Obeysekera et al. (2011) highlighted that the rise in sea levels due to climate change would result in an increase in floods, as well as the unreliability in terms of the expected benefit from the hydraulic structure constructed in the basins close to coastal regions would raise. With respect to probable extreme precipitation in the future, Giorgi (2006) pointed out that the Mediterranean basin (including Turkey) was one of the most sensitive regions. The previous studies dealing with climate variability in Turkey indicate that there is remarkable alteration in precipitation characteristic (Unal et al., 2012; Yurekli, 2015). In the context of precipitation, the most pronounced impact of global warming on the world has begun to be felt as floods and drought, the two of which are the most common and costly, compared to other natural disasters. Among the natural catastrophes occurred in Turkey, floods have given rise to the most deaths and economic losses after the earthquake (Ozcan, 2008). During the period 1948 to 2015, the flood events that have taken place in Turkey brought about 1350 fatalities and, economic losses estimated at US$ 2.195 billion, in addition to affecting 1.778520 people (Enginsu, 2015). Ozcan (2006) underlined that floods have

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commonly experienced in the Black Sea, Marmara, and Mediterranean regions in Turkey and the Black Sea region has been exposed to flood events more frequently. The 116 flood events in the period from 1956 to 2012, 80 of which occurred in the summer season, were experienced in the Middle Black Sea region under the study. About 4290 hectares of the cultivated area was damaged while these floods caused 29 casualties. Also, the 8051 homes and working places were totally exposed to undesirable conditions (Enginsu, 2015). There has been a considerable increase in flood events in the last 15 years.

Minimization or elimination of the damages resulted from floods is mostly realized with practices such as the construction of flood protection structures and cultural measures. The estimation of the design criteria associated with a hydraulic structure is based on the frequency analysis of the variable considered (Yurekli et al., 2011). In this respect, having knowledge on the frequency behaviour of available data in predicting the possible future magnitude of heavy rainfall is of crucial importance (Shahzadi et al., 2013). This would provide more reliable information about extreme events in the management and planning of water resources within a regional context. The design accuracy of the hydraulic structures is largely influenced by the adopted frequency analysis approach and the quality and quantity of the data used in the analysis. The lack or inadequacy of data to be analyzed is one of the most serious problems frequently encountered in achieving this goal (Easterling et al., 2000; Yurekli et al., 2009). To address this problem, hydrologists have focused their research on reliable analysis of available excess data for several decades (Ngongondo et al., 2011). In the cases where hydro-meteorological data is insufficient in terms of quantity and quality, the regionalization approach introduced by Hosking (1990) has shed quite important light on the solution to this problem. This approach, defined as regional frequency analysis and having several advantages over conventional moments, has been used frequently since the mentioned period for the assessment of extreme events (Anilan et al., 2016; Zakaria and Shabri, 2013). The realization of this approach is based on identifying the region, or finding the sites compatible with each other in a region, homogeneity test for the supposed region, and designating of the regional statistical distribution (Durrans and Kirkby, 2004).

Generally, the basic assumption taken into consideration while performing the frequency analysis of any hydrological variable is that the geomorphological and climatic conditions are stable over time in the region where the variable in question is measured. More importantly, when considered in the context of our globe under the threat of global warming, this issue is an important risk in estimating the reliable design criteria for any hydraulic structure. Although there are some studies discussing the effect of climate change on the frequency characteristics of hydrological variables in the literature (Hirsch and Ryberg, 2012; Cancelliere, 2017), it seems an inevitable fact that it is essential to focus more on studies on what would be the reaction in the case of the data having non-stationarity. In this regard, researchers are faced with the fact that the possibility of occurring unstable conditions in which hydrological variables are measured should be constantly kept fresh in their minds. With global climate change shifting the natural functioning of the hydrological cycle, non-stationary in the hydrological extreme series has been led to. As the estimation of design rainfall depth from the probability distribution fitting best to the rainfall extreme series being the main factor in taking place of floods is expected to alter due to global warming, it should be considered in their frequency analysis that the non-stationary condition is an important issue that cannot be ignored (Gregersen et al., 2013; Lee et al., 2016). From this perspective, before performing frequency analysis of extreme hydrological events, it is necessary to check whether the available data is stationary or not. In the case where there is a statistical significance trend in the data set, it is possible to transform the data into a stationary time series by using de-trending. However, it is recommended to carry out frequency analysis over non-stationary series (Razmi et al., 2017). The frequency analysis dealing with a non-stationary time series in the literature was commonly realized based on the time-varying moments (e.g., Katz, 2013; Cancelliere, 2017). Almost all of the studies on frequency analysis in the context of the impact of climate change have been carried out on the at-site data sets, and there have not been enough studies in terms of regional frequency distribution yet. In spite of the fact that several efforts have been made for regional frequency analysis (RFA) of heavy rainfalls for some parts of Turkey during the last decades (e.g., Anlı et al., 2009; Yurekli et al., 2009), there has not been a study evaluating the impact of climate change on frequency analyses in a regional and at-site context throughout Turkey yet. This study was implemented in the Middle Black Sea Region (MBSR), in which destructive flood events took place in the last years, in order to eliminate such a deficiency for Turkey and to contribute to the literature.

The specific objectives of the present study were: 1) to compute L-moments and its ratios from the actual data sequences 2) to check reliability of the data for the RFA, 3) to form groups of sites that satisfy homogeneity condition, 4) to choose regional frequency distribution, 5) to estimate quantiles based on the growth curve procedure for each homogeneous region, 6) to apply Innovative Trend Analysis (ITA) in detecting the increasing or decreasing trend in the annual maximum daily rainfall (AMR) data sequences, 7) to generate the AMR data set for each at-site by using the Monte Carlo resampling approach and to re-apply the L-moments algorithm to the simulated AMR data, 8) to identify variability between the AMR quantiles predicted separately from the actual and simulated data for the return periods.

2. Study Area and Data

Turkey is geographically separated into seven regions, one of which is the Black Sea region whose sub-sections are Western, Eastern, and Middle Black Sea. The geographical position of the Middle Black Sea Region (MBSR) selected as the study area is located between 39 and 43 north latitude and 34 and 38 east longitude. The annual mean temperature of the basin is 14°C, the

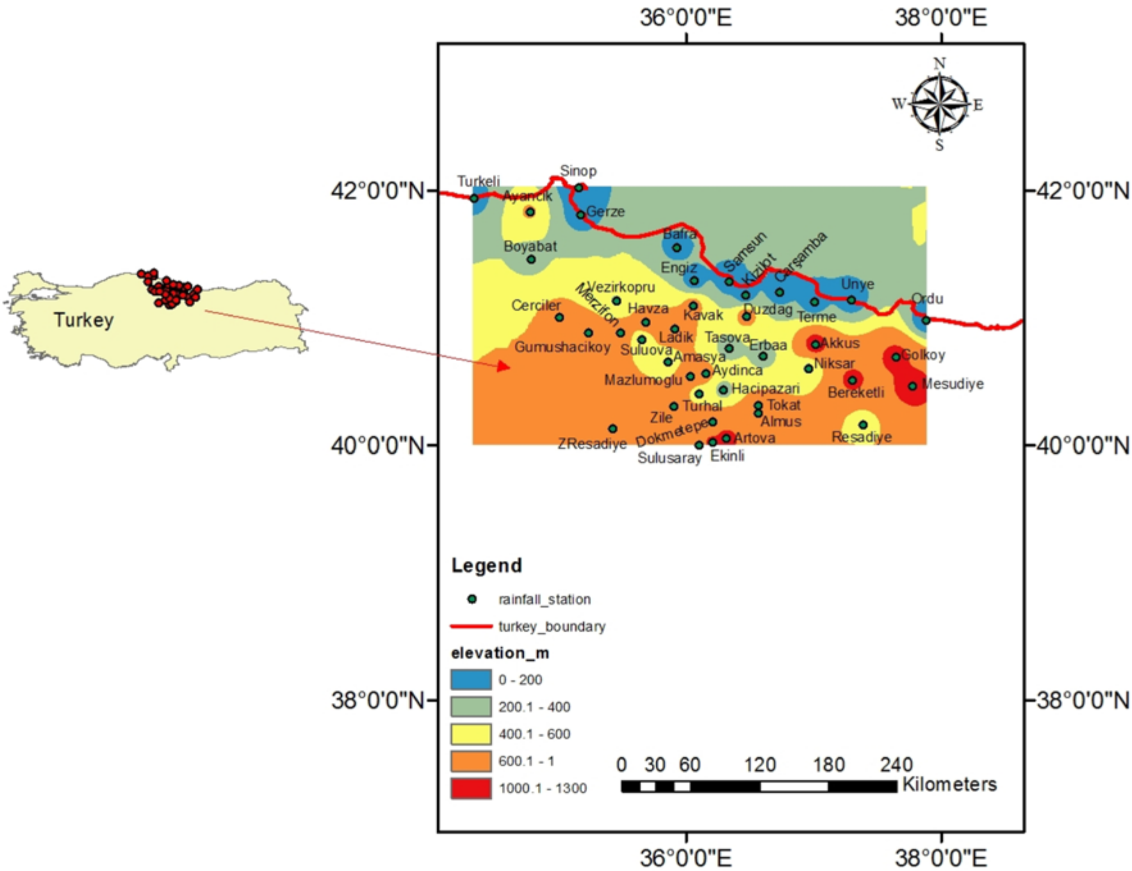

Fig. 1. Geographical Location of the Sites Over the Study Area

mean temperature in January is 7ºC and the mean temperature in July is 23ºC. The elevation characteristic of the region is highly variable, due to the connection of the northern part of the region with the Black Sea, and its inner parts with the Central Anatolian Geographical Region. In the context, the altitudes of the precipitation stations considered in the study vary from 5 meters (Ordu station) to 1287 meters (Akkus station). Corresponding to about 5.6% of Turkey's surface area to the study region has an area of 43 684 km^2. Within the boundaries of the MBSR, there exist plains such as Carsamba and Bafra on the coast and Erbaa, Tasova, and Suluova in the inner parts. Since the MBSR is situated within the boundaries of two major river basins, namely Kizilirmak and Yesilirmak, both rivers are among the main water resources of the region. Due to its geographical position, the MBSR is under the influence of two different climatic characteristics, one of which is a temperate Oceanic climate affecting the coastal area and the other of which is a continental climate reigning in the inland area. In terms of the amount of precipitation, significant differences are experienced from the coastal area to the inner parts. While annual rainfall varies around 600 – 800 mm in coastal areas, this amount decreases to 450 mm in inland areas. Although heavy rainfalls are frequently observed in the coastal areas in the autumn, it occurs in winter in the inner parts (Sozer et al., 1990). Large-scale atmospheric systems positioned over Eurasia and the North Atlantic has mainly become effective in the formation on climate characteristics of the Black Sea (Kosarev, 2008). With the above-mentioned variable topography and climatic characteristics, the MBSR was chosen as the study area for the purpose aimed in this study.

In the study, although 70 rainfall stations with different recording lengths, which are under the control of the Turkish State Meteorological Service and General Directorate of State Hydraulic Works, have been identified in the region, the stations with less than 30 years of observation periods were excluded from the analysis. Mckee et al. (1993) suggested using more than 30 years of data with continuous observation in the analysis. The rainfall station would be hereafter referred to as site. The rainfall data of the sites up to 2020 were taken into account in the study, although not every site has rainfall records until 2020. The geographical location of the sites over the MBSR is presented in Fig. 1 and, some features dealing with the sites are given in Table 1. The annual maximum daily rainfall amounts (AMR) of the mentioned sites formed the material of the study. The missing AMR amounts of the considered sites were completed with the normal-ratio method. The inhomogeneity condition and detection of change-point for the AMR data series of each station were performed with Mann-Whitney U, Standard Normal Homogeneity and Pettit approaches. Wijngaard et al. (2003) underlined that while the Standard Normal Homogeneity test is sensitive to detect breaks at the beginning and end of the data, the Pettit test is capable of detecting breaks in the middle part of the data. These approaches in question were applied for the determination of the breakpoint during the application of the double mass curve. The Double Mass Curve method was applied to the data sequences not satisfying the homogeneity condition. After the rainfall data sequences were put into the desired quality for regional frequency analysis, the realization of the regionalization procedure was briefly presented below.

3. Regionalization Procedure

This procedure based on Linear moments (L-moments) is performed in three stages, which are the choice of an initial region, the application of heterogeneity analysis to the region, and the selection of the most appropriate regional distribution for the region fulfilling the condition of homogeneity. All details of these phases are available in Hosking and Wallis (1997) and, Rao and Hamed (2000) More recently Adib and Marashi (2019) used SPI to investigate meteorological drought of different time scales in western Iran and employed cluster analysis to determine homogeneous regions and utilized L-Moment method to find the best regional probability distribution. For regional frequency analysis and identification of homogenous regions, Adib et al (2021) used the L-moment method, the homogeneity test and cluster analysis. for monitoring hydrological drought in Khuzestan Province in Iran. In this respect, highly summarized information about these stages has been given in the present study.

Choosing an initial region is considerably based on the characteristics of the sites, which are necessary for grouping methodology such as clustering analysis, as well as the experiences on the region. The first effort for this purpose in almost all studies was to examine whether the region studied is the only region in terms of homogeneity. To decide homogeneity of any region, L-moments being the linear combination of the probability-weighted moments for each site are firstly calculated, and then the L-moments ratios (L-CV, L-CS, and L-CK) respectively corresponding to Coefficients of Variation (L-CV), Skewness (L-CS), and Kurtosis (L-CK) are determined by proportioning the L-moments to each other. The first treatment to the region to be scrutinized for its homogeneity should be to detect the presence of the discordant site(s) within the region. Detection of the discordant station is determined by the discordancy measure, the relationship of which is given below.

$$D_i = 3^{-1}N(u_i-\bar{u})^T S^{-1}(u_i-\bar{u}) \tag{1}$$

$u_i = [t^i, t_3^i, t_4^i]^T$ including sample L-moment ratios of site i, where D_i is discordancy measure, t, t_3, and t_4 in the u_i vector correspond to L-CV, L-CS, and L-CK, respectively. In equation, N is the number of sites within the region. If $D_i > 3$ for any site i, the site is considered as discordant. In case of the presence of the discordant station(s), the station(s) in question are assigned to another sub-region.

The heterogeneity analysis is dealing with a process applied to decide whether the region not having discordant sites is truly homogeneous. This analysis (H) is associated with the idea that the population L-moment ratios of the region are like to be close to the average of the sample L-moment ratios of each site data in the region. Therefore, this test provides the judgment of whether sites in a group form a homogeneous region. The "H measure is estimated on the L-moment ratios (L-CV, L-CS and L-CK). But, the heterogeneity measure taking into account only the L-CV was used in this study. Hosking and Wallis (1997) underlined that the heterogeneity measure predicted depending upon L-CV had much better discriminative capability in confirming the homogeneity of the region than the other heterogeneity measures in which the L-CS and L-CK in their calculations were considered. In the estimation of this measure, the data of 500 homogeneous regions simulated by population parameters equivalent to the regional average of L-moment ratios of the sites in the region where homogeneity is expected are mainly used. The *H* statistic is obtained by;

$$H_1 = \frac{v-\mu_v}{\sigma_v}, \tag{2}$$

In Eq. (2), the values of V, μ_v (average) and σ_v (standard deviation) are calculated based on the sample L-moment ratios and the L-moment ratios of the simulated 500 homogeneous regions, respectively. According to the result of the H statistic, a judgment is made about the homogeneity of the selected region, which is homogeneous if $H < 1$, possibly heterogeneous if $1 \le H < 2$, and definitely heterogeneous if $H \ge 2$.

The process of determining the regional distribution is to find out the regional distribution best representing the data sequences of the sites in the group statistically confirmed to be a homogeneous region. The best distribution for the homogeneous region is chosen in accordance with the goodness-of-fit-test, called Z^{DIST}. The test process is achieved based on the difference between the L-CK of candidate distribution and the average L-CK of the homogeneous region. The goodness-of-fit-test is realized by;

$$Z^{DIST} = (t_4^{DIST} - t_4^R + \beta_4)/\sigma_4 \tag{3}$$

In the equation, t_4^R is the regional average of the L-CKs belonging to the sites in the homogeneous region, DIST represents the candidate probability distribution, β_4 is the bias associated with the regional average of the at site L-CKs, σ_4 is the standard deviation of regional average sample L-CK. The β_4 and σ_4 are estimated based on the 500 regions simulated very similar to the homogeneous region by using the four-parameter Kappa distribution. In the case where one or more of the considered distributions have the $|Z^{DIST}| \le 1.64$, these distributions are chosen as regional distribution. But, the distribution with the numerically smallest $|Z^{DIST}|$ value among them is preferred as the best-fit distribution.

Prediction of quantile is implemented on the well-known approach of Dalrymple (1960), called as index-flood and index-storm depending upon analysing either streamflow or rainfall. The index-storm method will be hereafter used in the present study due to the use of rainfall data as material. This approach has been widely used in regional and at-site quantile estimates associated with hydro-meteorological data. This method is based on the assumption in which the sites forming a homogeneous region have an identical statistical distribution apart from index streamflow or rainfall value (a site-specific scaling factor) (Hosking and Wallis, 1997). Mathematically, the quantile estimates at site i for a region with N sites are calculated by

$$Q_i(F) = \mu_i q(F) \tag{4}$$

where μ_i is index rainfall (a site-specific scaling factor) value for site i, F is non-exceedance probability, and q is dimensionless distribution function (growth curve).

4. Detecting Change in Time Series

In addition to the parametric (linear regression method) and non-parametric (Mann-Kendal and Spearman Rho) approaches, which were widely used in the literature to reveal the change in time series, the Innovative Trend Analysis method (ITA), which includes a different application structure, has frequently preferred in scrutinizing variability in hydro-meteorological data sets since it was introduced by Şen (2012). In the studies comparing the ITA with other trend analysis methods (Güçlü, 2018; Wang et al., 2020; Yurekli, 2021), this approach was highlighted to be much more effective in identifying the variability in time series sequences. The basic assumption of this method is that the scattering positions of the two time series in ascending order relative to each other around a line inclined 45 degrees in the Cartesian coordinate system allow judgment about the change in the relevant data sets. More detailed information on this approach is available in Yurekli (2021). In the light of the general information explained above, when applying the ITA methodology, testing whether the change in the available time-series data is statistically significant according to ITA is based on the averages of the two halves obtained from dividing the data. The null hypothesis of the ITA statistical significance test is accepted in the case where the calculated slope (S_{cal}) is under the critical slope value (S_{crit}) at the 5% significance level. The value (1.960) of the S_{crit} is obtained from the Standard Normal Distribution Table.

Although the common approach is based on the assumption that the data to be used in the analysis is stationary in the estimation of the design value used in the construction of hydraulic structures, it would be a more realistic approach to consider the possible non-stationary conditions of hydro-meteorological time series due to climate change. In the study, the AMR data for each at-site was generated by using the Monte Carlo simulation technique to explore frequency distribution behaviour belonging to the data of interest under non-stationary conditions. While applying this simulation method for each at-site, the regional distribution selected to be the most suitable to the homogeneously accepted region, based on the L-moments method, as well as the magnitude of the trend estimated by ITA (whether statistically significant or not, after all, it gives information about the general course of the data), were used. Thus, considering its own internal dynamics for each data, the effect of non-stationary conditions expected to occur in the future on frequency analysis was tried to be determined. The reason why the regional distribution was chosen for the Monte Carlo simulation is that it represents the data of all sites in the relevant region. As known, the basis of the regionalization approach is based on the assumption that the stations in the homogeneous region have similar frequency distribution behaviour. And then, the L-moments algorithm, whose methodology was explained above, was re-applied to the AMR data simulated for the sites selected for regional frequency analysis in the MBSR. This would allow us to distinguish the difference between regional distributions selected as the best fit, and regional and at-site quantity estimations in the context of observed and simulated data.

5. Results and Discussions

In the study, first of all, it was focused on whether the rainfall datasets (AMR) in the stations were suitable for reaching the targeted purpose. As a first effort, the relevant data of the stations with missing data were completed with the normal-ratio method, which was widely preferred in the literature. After this process, the AMR data of each station was analyzed with the effective and non-parametric Mann-Whitney U test, which was frequently preferred to decide on the homogeneity of hydrological data. The Mann-Whitney U test results revealed that there was inhomogeneity in the AMR data belonging to Niksar, Taşova, Amasya, Aydınca, and Gölköy stations. Also, detection of change-point at these stations was achieved with Standard Normal Homogeneity and Pettit approaches, which were widely used in the literature. The years of change for the stations in question were 1972, 1985, 1973, 1983, and 1972, respectively.

After calculating the low-order L-moments and its ratios for the data sequences (annual maximum daily rainfall, AMR) of each site in The Middle Black Sea Region (MBSR), as mentioned above, the first step in the regionalization procedure was to explore whether the entire study area could be treated as a homogeneous region. The discordancy measure, which is an indicator of the inter-site consistency in the region, revealed the existence of a discordant station (Bereketli). In case these station was removed from the group, none of the remaining stations in the area appeared discordant. The heterogeneity test effort, which is the next step in regionalization, showed that the whole region not covering this station should definitely be evaluated as heterogeneous. In fact, it is possible to estimate that this result could be reached from Table 1. The reason for this is that the topographic conditions of the sites in the region seem an obstacle to considering the entire region as a single homogeneous region. Similarly, the diagrams of L-moment ratios (the L-CV versus L-CS and L-CS versus L-CK) have also supported the judgment in question owing to quite high scattering in L-moment ratios. Based on the above–described methodology of regionalization, the prevalent effort under conditions where the requirements for regional frequency analysis could not be performed is that it is the division of the whole region into subgroups (sub-regions) until being satisfied all of the prerequisites. Regarding the division into sub-regions, Hosking and Wallis

Table 1. Geographic Characteristic of the Stations (sites) in the Study Area

Site Code	Sample Size	Station Name	Elevation (m)	Latitude (°N)	Longitude (°E)
R11	88	Tokat	608	40.31	36.56
R12	59	Almus	830	40.25	36.56
R13	51	Artova	1,200	40.05	36.31
R14	49	Erbaa	230	40.70	36.60
R15	67	Niksar	350	40.60	36.96
R16	34	Resadiye	450	40.16	37.38
R17	38	ZResadiye	790	40.13	35.42
R18	35	Sulusaray	950	40.00	36.10
R19	63	Turhal	500	40.40	36.10
R110	62	Zile	700	40.30	35.90
R111	30	Akkus	1,287	40.79	37.01
R112	50	Dokmetepe	635	40.18	36.20
R113	31	Ekinli	1,070	40,02	36.20
R114	31	Hacipazari	220	40.43	36.29
R115	52	Tasova	200	40.76	36.33
R116	42	Mesudiye	1,191	40.46	37.77
R217	85	Amasya	412	40.65	35.85
R218	35	Aydinca	675	40.56	36.15
R219	43	Gumushacikoy	770	40.88	35.23
R220	33	Havza	750	40.96	35.68
R221	49	Ladik	950	40.91	35.91
R222	92	Merzifon	755	40.88	35.48
R223	47	Suluova	490	40.83	35.65
R224	54	Mazlumoglu	870	40.54	36.03
R225	30	Kavak	741	41.09	36.05
R226	38	Vezirkopru	377	41.13	35.45
R227	31	Cerciler	700	41.00	35.00
R228	30	Bereketli	1,125	40.51	37.30
R329	92	Samsun	15	41.28	36.33
R330	57	Carşamba	35	41.20	36.73
R331	92	Ordu	5	40.98	37.88
R332	39	Golkoy	1,158	40.69	37,64
R333	66	Unye	16	41.14	37.29
R334	34	Terme	10	41.12	37.00
R335	50	Kizilot	10	41.18	36.46
R336	30	Duzdag	800	41.01	36.47
R337	89	Sinop	32	42.02	35.15
R338	40	Ayancik	630	41.83	34.77
R339	30	Gerze	86	41.81	35.17
R340	68	Bafra	103	41.55	35.92
R341	30	Turkeli	127	41.94	34.33
R342	50	Engiz	25	41.29	36.06
R343	60	Boyabat	350	41.46	34.78

(1997) suggested the Ward's clustering algorithm. In addition, having preliminary information about the region also contributes to the decision process related to the subgrouping. Considering the Ward's clustering algorithm and the preliminary information on the study area, it was concluded that two or more sub-regions should be formed. The regionalization process was not achieved in the trial of two sub-regions. The separation of the whole region into three sub-regions revealed discordance for none of the sites in the three regions while the heterogeneity test results dealing with the sub-regions indicated homogeneity. After the homogeneity of the sub-regions was statistically approved, the most appropriate regional distribution for each region was determined based on the goodness-of-fit-test (Z^{DIST}). Generalized Extreme Values (GEV) for two sub-regions, Generalized Logistic (GLOG) for the other sub-region were found to be the most appropriate distributions. The regionalization analysis results associated with the three sub-regions were presented in Table 2.

The Innovative Trend Analysis (ITA) approach was implemented to detect increasing or decreasing change in the AMR data sequences, after dividing all of the data sets belonging to the sites into the halve for the application of the ITA test. The ITA test materialized on the data of the 43 sites revealed that approximately 67% of the rainfall time series in the studied area showed an upward change while the remaining data sets (about 33%) had a downward change. As can be seen from Table 2, the data sets of six sites (given in bold characters) put forward a statistically insignificant change. The statistically insignificant trends were detected in the two data sets for the sub-region I and in the four data sets for the sub-region III, respectively, whereas there was a statistically significant trend in all of the AMR data sets in the sub-region II. Surprisingly, it was found that 25% of the sites in sub-regions I and II and, nearly half of the sites in sub-region III had a downward change. Nemli (2017) underlined that there was an upward trend in the maximum rainfalls recorded in the Eastern Black Sea region. Ay (2020) reported having an increasing trend of monthly total rainfalls obtained from most of the considered stations in the Western Black Sea region. Balov and Altinkaynak (2019) stated to be more probable for short duration and heavy precipitation events to take place in the future periods, based on the extreme rainfall indices sequences formed by using the observed and simulated data at nine sites in the Western Black Sea Basin. The finding by Sen et al. (2012) for the eastern part of the Black Sea region as well as northeastern Turkey was that precipitation might increase by 25%. The findings of the present study are consistent with these previous studies.

Considering the best appropriate distributions selected for sub-regions formed for the observed AMR data, the 5000 AMR data were simulated for each site by using the Monte Carlo approach in order to examine the influence of non-stationarity in frequency analysis. The magnitude of the trend calculated by the ITA procedure for each site was multiplied by the simulated data and added to the simulated data, and thus the effect of the trend was included in the data. This way followed in the study allowed the real variability of each data to be reckoned with directly in the analysis. The L-moments algorithm was re-applied for the three sub-regions, with the simulated data including the trend. Although none of the sites in each sub-region has discordancy, all of the sub-regions showed heterogeneity definitely since the

Table 2. The Regionalization and ITA Results Associated with Sub-Regions

Sub-Region I			Sub-Region II			Sub-Region III		
Site	Di	S_{cal}	Site	Di	S_{cal}	Site	Di	S_{cal}
Tokat	0.23	-0.069	Amasya	0.18	0.023	Samsun	0.69	**-0.013***
Almus	0.20	-0.126	Aydinca	0.84	0.268	Carsamba	0.80	**0.020***
Artova	1.52	0.098	Gumushacikoy	1.39	0.210	Ordu	1.09	-0.126
Erbaa	0.30	0.142	Havza	0.46	0.370	Golkoy	1.81	0.349
Niksar	0.44	0.091	Ladik	1.22	-0.251	Unye	1.96	**-0.003***
Resadiye	1.37	0.101	Merzifon	0.27	0.056	Terme	0.67	0.946
ZResadiye	2.90	0.281	Suluova	0.26	0.197	Kizilot	0.52	0.484
Sulusaray	0.28	0.378	Mazlumoglu	1.63	-0.151	Duzdag	1.69	0.461
Turhal	0.18	0.149	Kavak	2.18	0.028	Sinop	0.56	-0.086
Zile	0.36	0.071	Vezirkopru	0.74	0.179	Ayancik	1.57	0.304
Akkus	0.72	-0.396	Cerciler	0.76	-0.012	Gerze	0.78	0.217
Dokmetepe	0.72	0.239	Bereketli	2.07	0.058	Bafra	0.75	-0.127
Ekinli	1.70	0.252				Turkeli	0.69	**-0.131***
Hacipazari	2.09	**0.068***				Engiz	0.74	-0.295
Tasova	0.75	0.150				Boyabat	0.67	0.371
Mesudiye	2.25	**-0.014***						
Heterogeneity (H)		0.15	Heterogeneity (H)		-0.09	Heterogeneity (H)		0.69
Z^{GLOG}		-0.12	Z^{GEV}		-0.36	Z^{GEV}		-0.75

Di, Discordancy measure for site i
GLOG, Generalized Logistic Distribution
GEV, Generalized Extreme Values Distribution
S_{cal}, trend slope at 5% confidence level based on the ITA approach
*, statistically insignificant trend

H measures representing regional heterogeneity were 2.17, 3.92 and 6.5, respectively. This result means that the region has turned into a more heterogeneous structure with the effect of the trend in rainfall data. Under these circumstances (due to natural or human-induced effects), the way to be followed in order to realize regional frequency analysis should be to arrange new sub-regions instead of existing homogeneous sub-regions. The scatter plots against each other of each L-moment ratio (L-CV, L-CS, and L-CK) obtained from the observed and simulated data were illustrated in Fig. 2. The L-CV scatter plots for sub-regions II and III showed a downward change in the L-CV values of the sites in these regions, whereas there was a more stationary structure for the sub-region I. The statistical significance test based on the ITA also approved the decreasing variability in the L-CV values of the simulated data related to the sub-regions II and III. But, this statistic test found that there was insignificant upward change in the L-CVs for the sub-region I. These findings related to L-CVs are evidence supporting the heterogeneity results of the sub-regions. The scattering behavior of other L-moment ratios (L-CS and L-CK) was not as pronounced as in L-CV, especially in L-CS. It was not possible to visually conclude about the existence and direction of change from the L-CS scatter plots of the three sub-regions. However, the statistical significance test by the ITA approach revealed that there was an increase in sub-regions I and II, and a decrease in sub-region III. In this sense, the variability in sub-regions I and II was found statistically significant. The L-CK scatter graphs concerning with all sub-regions exposed visually the existence of an upward change in the low L-CKs. It was detected that there was a statistically significant increasing change in the L-CKs of the first two regions, while there was a statistically insignificant downward variation in that of the sub-region III. All these findings clearly demonstrate the effect of the trend on the AMR data.

In order to reveal the quantitative variability in the estimated quantiles under the cases where non-stationarity exists in the data to be used for the frequency analysis, the L-moments algorithm was re-applied the simulated data from the Monte Carlo approach. The efforts have been made to ensure that each of the sites, whose L-moment ratios were calculated from the simulated data, were members of any sub-homogeneous region. Although the Kavak site was assigned to many sub-regions, this site provided homogeneity in none of the sub-regions, however, its discordancy remained below the critical value in almost all sub-regions. This site was excluded from the non-stationarity comparison. The fact that this site has a very small L-CV value, compared to other sites, can be seen as the reason for this discarding. Based on the simulated data in the MBSR, only in the case of five sub-regions, all conditions of the L-moments algorithm could be satisfied. The relevant results are given in Table 3. In fact, these findings revealed that the changes experienced in the rainfalls of the sites in the region rose up the regional heterogeneity. To further elaborate these results, the quantiles estimates were realized at the different

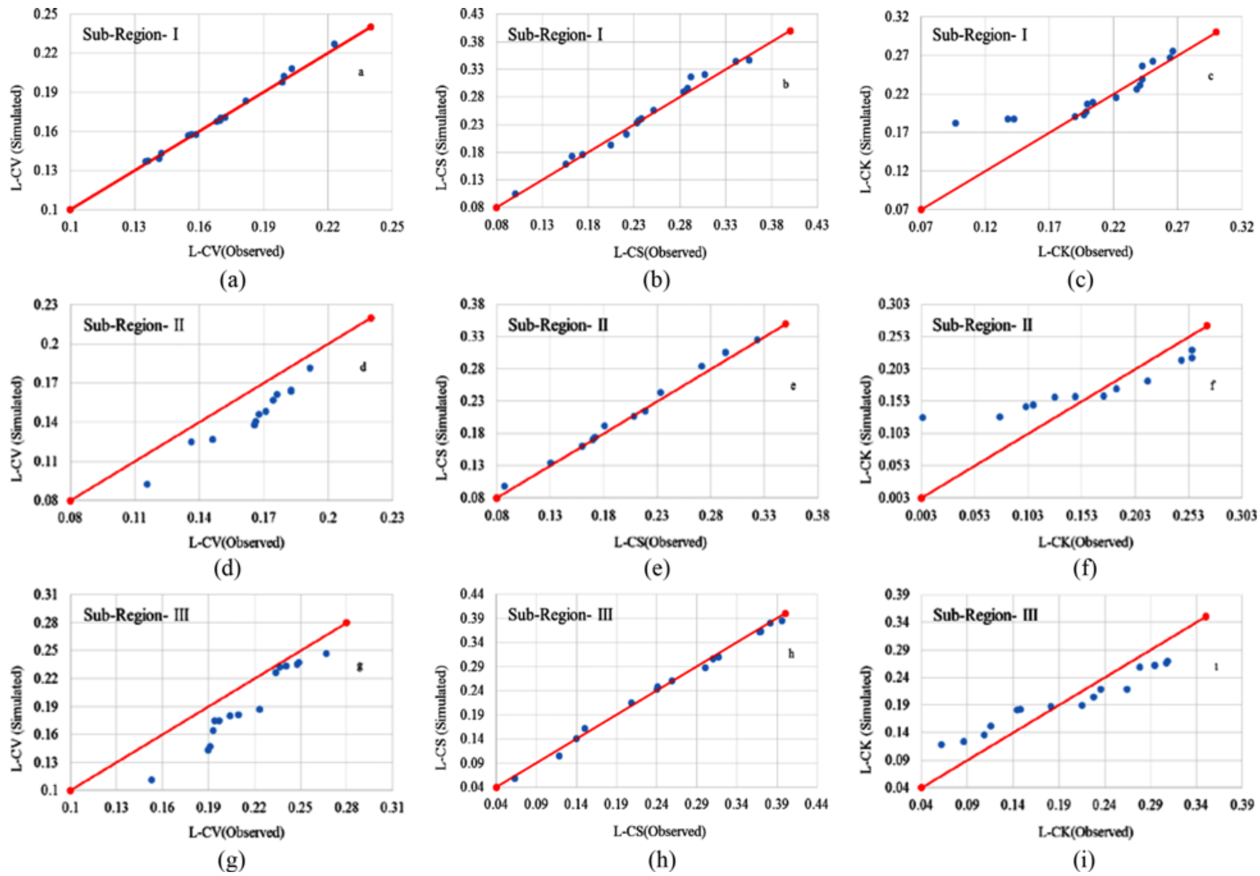

Fig. 2. Scatter Plots of Observed and Simulated L-Moment Ratios: (a) Sub-Region I: L-CV, (b) Sub-Region–I: L-CS, (c) Sub-Region-I: L-CK, (d) Sub-Region II: L-CV, (e) Sub-Region II: L-CS, (f) Sub-Region-II: L-CK, (g) Sub-Region III: L-CV, (h) Sub-Region–III: L-CS, (i) Sub-Region-III: L-CK

Table 3. The Regionalization Results Dealing with Monte Carlo Simulation

Sub-Region I		Sub-Region II		Sub-Region III		Sub-Region IV		Sub-Region V	
Site	Di	Site	Di	Site	Di	Site	Di	Site	Di
Tokat	2.16	Almus	0.20	Amasya	0.39	Gümüshacikoy	0.52	Samsun	0.68
Artova	1.57	Erbaa	1.14	Aydinca	0.97	Ladik	1.35	Kizilot	0.35
Niksar	0.49	Akkus	0.95	Havza	0.54	Suluova	0.44	Unye	1.69
Resadiye	0.58	Hacipazari	1.42	Merzifon	1.46	Vezirkopru	1.39	Sinop	0.78
ZResadiye	2.32	Tasova	0.86	Mazlumoglu	1.02	Cerciler	1.28	Gerze	1.02
Sulusaray	0.11	Mesudiye	0.86	Ayancik	1.61	Bafra	1.02	Turkeli	1.31
Turhal	0.27	Carsamba	1.46					Engiz	1.33
Zile	0.62	Ordu	1.48					Boyabat	0.86
Dökmetepe	0.08	Golkoy	0.34						
Bereketli	2.14	Terme	1.24						
Ekinli	0.67	Duzdag	1.06						
H	-0.65	H	0.80	H	0.97	H	-0.40	H	0.55
Z^{GLOG}	-0.16	Z^{GLOG}	0.28	Z^{GEV}	-0.07	Z^{GEV}	-0.48	Z^{GEV}	-0.41

return periods by using the index-storm approach for each station in the context of both observed and simulated data. This activity was finalized as a result of the most appropriate distribution decided for the region where the relevant site was appointed. Fig. 3 is related to a quantitative comparison of observed and simulated data (difference of two quantities) at some return periods for non-exceedance probability, namely 1, 2, 20, and 100 years. The figure presents very clear proof of how different the frequency analysis results of the sites in each homogeneous region decided based on the observed data is. This difference has become

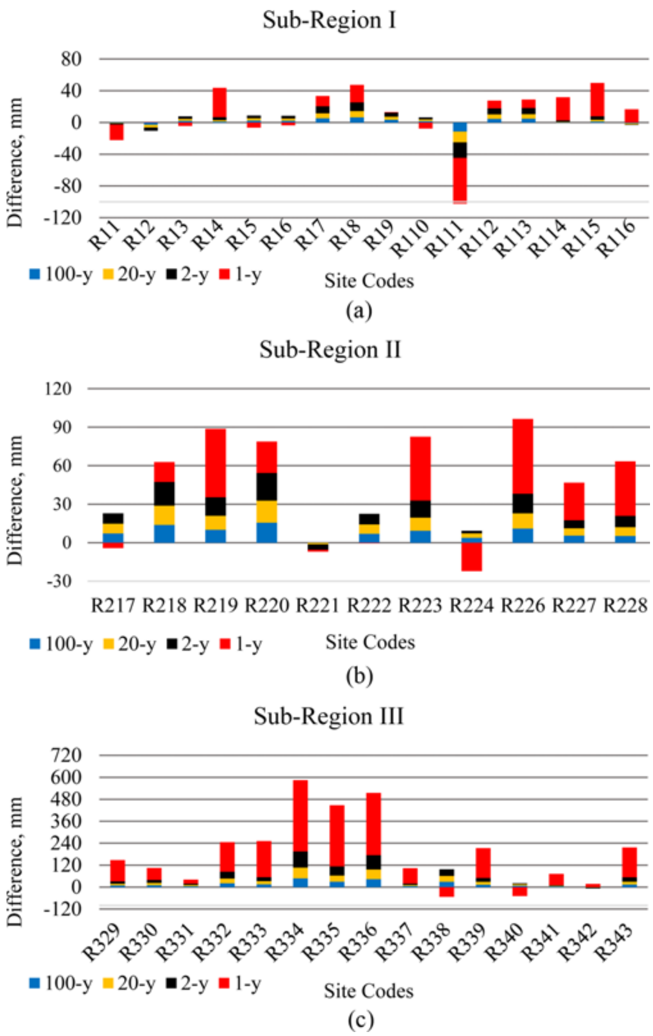

Fig. 3. Comparison of the Observed and Simulated Quantiles for Sites: (a) Sub-Region I, (b) Sub-Region II, (c) Sub-Region III

particularly much more pronounced in the quantile estimation of the 1-year return period. Even more interestingly, the effect of non-stationarity was more evident in the sub-region III.

On the other hand, revealing how the regional frequency distribution would react under non-stationary conditions is also among the main objectives of this study. As can be seen from the above findings, it was not possible to make such a comparison for the three sub-homogeneous regions belonging to the observed data, since the same homogeneous regions could not be formed with the simulated data. The possibilities of forming homogeneous regions with the same sites in the MBSR, using the observed and simulated data were investigated to find an answer to what extent the regional frequency distribution behaviour would change when there is the non-stationarity in rainfall data. In this sense, three homogeneous regions were made up to represent the whole region, and the L-moment algorithm results belonging to them were presented in Table 4. Ten stations were assigned to the first

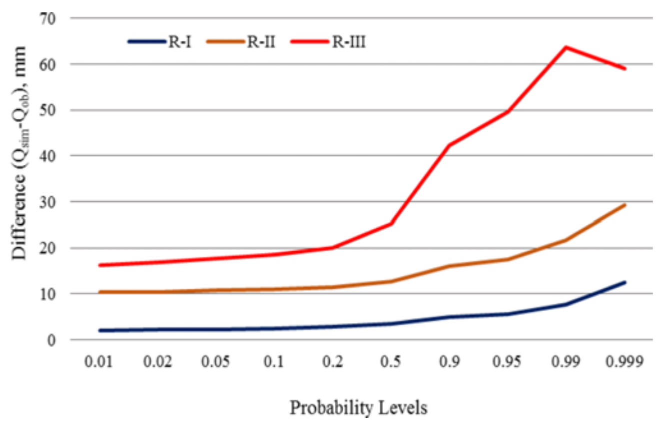

Fig. 4. Variation of Deviation between Regional Quantiles Based on Observed and Simulated Data

Table 4. Comparison of Regional Quantiles at Non-Exceedance Probability Levels

Probability Levels	Region I (R-I)			Region II (R-II)			Region III (R-III)		
	Sites	Q_{ob}	Q_{sim}	Sites	Q_{ob}	Q_{sim}	Sites	Q_{ob}	Q_{sim}
0.01	Tokat	17.0	19.0	Amasya	17.0	27.3	Samsun	25.2	41.4
0.02	Almus	18.2	20.3	Aydınca	18.3	28.7	Ordu	27.1	44.0
0.05	Erbaa	20.3	22.6	Gumuşhacikoy	20.3	31.1	Unye	30.5	48.2
0.1	Niksar	22.3	24.8	Havza	22.4	33.4	Terme	34.2	52.8
0.2	Resadiye	24.9	27.7	Merzifon	25.2	36.7	Kizilot	39.3	59.3
0.5	Sulusaray	30.7	34.1	Suluova	32.0	44.6	Sinop	51.8	77.0
0.9	Turhal	44.9	49.8	Mazlumoglu	47.8	63.8	Gerze	88.6	130.9
0.95	Zile	51.8	57.3	Vezirkopru	54.2	71.7	Engiz	108.6	158.2
0.99	Dokmetepe	71.9	79.6	Cerciler	69.2	90.9	Boyabat	175.4	239.1
0.999	Tasova	117.6	130.0		91.9	121.2		358.7	417.8
Heterogeneity (H)		-0.74	0.08	H	-0.81	0.99	H	-0.68	0.59
Z^{DIST}		Z^{GLOG} -0.65	Z^{GLOG} -0.46	Z^{DIST}	Z^{GEV} -0.77	Z^{GEV} -0.29	Z^{DIST}	Z^{GLOG} 0.27	Z^{GEV} -0.39

Q_{ob}, the quantiles obtained from the observed rainfalls
Q_{sim}, the quantiles obtained from the simulated rainfalls

of these sub-regions and nine to the others. The quantiles predicted based on the simulated data compared to that of the observed data of three homogeneous regions sampled in order to detect the effect of non-stationarity in regional frequency analysis were found to show a nonlinear increase with increasing probability levels. This difference became more pronounced, especially from the 90% probability level. Moreover, the instability in all probability levels for Region III was much greater than the results of the other two regions. On the other hand, the inconstancy among quantile estimates belonging to Region II was also significantly different from that of Region I. The visual presentation of these findings was given in Fig. 4.

6. Conclusions

It is of great importance to reliably obtain the design value required in the construction of any hydraulic structure in terms of providing the expected benefit from the relevant structure. This request can be realized if data suitable for the purpose is found. While estimating the design value, the frequency analysis based on the available data is carried out with the assumption that the existing data is obtained under stationary conditions. However, climate change, which has affected the globe since the middle of the 20th century, has led to the formation of non-stationary conditions for hydro-meteorological variables. Performing frequency analysis by acting as if there is stationarity in the presence of non-stationary conditions would be an obstacle to the reliable design of water-related structures. The current study was conducted to evaluate the impact of non-stationary conditions on regional and site-based frequency analysis of annual maximum daily rainfall (AMR) data sets of the 43 rainfall stations (sites) on the Middle Black Sea Region (MBSR). The L-moments algorithm, Innovative Trend Analysis (ITA) and Monte Carlo Simulation were used to achieve this goal. The main judgments deduced from the study are briefly listed below.

1. Using the actual AMR (annual maximum daily rainfall) data of 43 sites, it was decided that the whole region was divided into three subgroups as the most optimal alternative where all phases of the L-moment algorithm were successfully implemented. It was concluded that GEV (Generalized Extreme Value) and GLOG (Generalized Logistic) distributions for three regions were the most suitable in performing regional frequency analysis.
2. An increasing trend has been detected in approximately two-thirds of the sites in the study area. This finding was consistent with previous studies of Nemli (2017), Ay (2020), Balov and Altinkaynak (2019) and Sen (2012). On the other hand, the data of only six sites showed a statistically insignificant change. The AMR data of all sites in Region II indicated the presence of statistically significant change. The more interesting finding in this sense is that almost half of the sites in Region III, which is much closer to the Black Sea coast than the other two regions, had a downward trend. Whereas a quarter of the sites in the remaining regions showed a decreasing trend. These results are very clear evidence that fulfilling frequency analysis assuming that the available data are stationary will fail to project reliable water-related structures.
3. The data sets produced by Monte Carlo simulation of each site in the three regions, taking into account the selected regional distributions based on the original data, were reconstructed with the magnitude of the trend calculated by ITA. Based on the L-moment ratios of simulated data, it was necessary to form five homogeneous regions. Synthetic L-CVs of the sites in the three homogeneous regions in the original data case compared to that of the actual values indicated a statistically significant decreasing change in sub-regions II and III. On the other hand, the synthetic L-CVs of the sites in the remaining region showed a statistically insignificant increasing change. In line with this result, based on the simulated data, the predicted heterogeneity measure (H) values for sub-regions II and III were obtained much greater than those of sub-region I. It proves that the variability in these two regions is greater. However, the change in other L-moment ratios (L-CS and L-CK) was not as pronounced as in L-CV, especially L-CSs. This change in L-moment ratios indicated that three sub-homogeneous regions separated by the original data could not remain stable. It was emphasized that when the region was divided into five sub-groups, homogeneous region conditions could be achieved. The increase in the number of sub-homogeneous regions from 3 to 5 indicates that the region has evolved towards a more heterogeneous structure.
4. When the quantile estimates of each site were compared over the regional distributions on the basis of actual and simulated data, it has been found out that there were very distinct differences towards a one-year return period (or 99.9% non-exceedance probability level). The non-stationarity was more pronounced at the sites of sub-region III.
5. Comparing the regional quantile estimates over the regional distributions decided in the context of the observed and synthetic data could not be performed due to the difference in the number of sub-regions and the sites not being the same in these regions. However, due to the necessity to answer this question, which is among the hypotheses of the present study, the possibility of forming homogeneous sub-regions with the same sites based on both data (the case where not all stations in the study area could be included) was investigated. For this purpose, considering the stations in three homogeneous regions formed with actual data, two sub-regions, which provided that the stations in them are the same, separately with the observed and simulated data were sampled for each sub-region. And then, quantile estimates based on selected regional theoretical distributions were realized for the two sampled sub-regions associated with each sub-region to scrutinize variability in regional frequency distribution under non-stationary conditions. It was ascertained that there were significant nonlinear

differences between the quantile estimates of the simulated and observed data belonging to the three sampled homogeneous regions in response to the increase in probability levels.

The points experienced and suggested by this study are as follows: By taking this study as a reference, researching using different simulation techniques in regions where the observation period at stations are longer and the data number is close to each other in almost all stations, would contribute to being had an idea about how the frequency distribution behaviour is affected under non-stationary conditions. In addition, by defining the variability in the existing data with different methodologies (different from the one in this study), it can be determined how the regional and site-based frequency distribution characteristics are affected by the methodology followed in this study.

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