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Frequency analysis of annual maximum precipitation under non-stationary conditions

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Abstract: In the present study, precipitation under the non-stationary conditions, driven by climate change, were modelled using a range of probability distribution functions. Trend tests were conducted on annual maximum precipitation data. Decreasing trends were observed at many stations and only two stations displayed increasing trends. Generalized Extreme Value (GEV) distributions, with both stationary and non-stationary parameters, were fitted to the time series obtained from various stations across Aegean Region. The parameters of the GEV distribution and the estimated return levels for various return periods were computed utilizing the exTremes and ismev packages within the R Studio open-source platform. The best models were selected using the Akaike information criterion (AIC) and Bayesian information criterion (BIC) The analysis revealed that for the trend observed stations, distributions with non-stationary parameters offer a more accurate representation of the hydrologic processes.

Key words: Frequency analysis; non-stationary frequency analysis; standard duration annual maximum precipitation; trend; generalized extreme value distribution.

1. INTRODUCTION

Climate change has led to significant shifts in the frequency and intensity of extreme hydrological events. These evolving phenomena challenge traditional frequency analysis, based on the assumption of stationarity (Milly et al., 2008). Stationarity, which underpins methods like return period analysis, assumes that hydrologic conditions are constant over time and lack long-term trends (Katz et al., 2002). However, emerging evidence suggests that this assumption may no longer hold as climate variability introduces changes to precipitation patterns (Sveinsson et al., 2003).

Given the observed acceleration of hydrological cycles and the predicted impacts of climate change on extreme events, non-stationary frequency analysis has gained importance. This approach allows for temporal variability in hydrological processes, incorporating time-varying parameters into statistical models (Katz & Brown, 1992). Research shows that non-stationary models can better capture the complexities of extreme events under changing conditions, making them critical for future water resource planning (Villarini et al., 2009; Cunderlik & Burn, 2003).

In the presented study, time series of observed annual maximum precipitation data for standard durations (t = 5, 10, 15, 30 minutes, and 1, 2, 3, 4, 5, 6, 8, 12, 18, 24 hours) from eight central meteorological stations in the Aegean Region were analysed for trends. To achieve this, non-parametric Mann-Kendall and Spearman's Rho tests, as well as the parametric Student's t-test, were applied. For modelling and prediction, Generalized Extreme Value (GEV) distributions were fitted to the time series under both stationary and non-stationary assumptions across all periods. The GEV model was initially calculated under stationary assumptions, with the distribution parameters held constant, and precipitation return levels were derived for each period. In the first non-stationary model (GEV1), the scale parameter was modelled as a first-order function of time. In the second model (GEV2), the location parameter was modelled as a first-order function of time. In the third model (GEV3), both the scale and location parameters were modelled as first-order function of time and the corresponding return levels were calculated. In all models, the shape parameter was kept constant. Model selection was based on the Akaike and Bayesian Information Criteria to identify the most suitable model for the process. Return levels of extreme precipitation for various periods were subsequently determined for both stationary and non-stationary models. The objective of this study is to identify the most accurate model for representing hydrological processes in the context of climate change.

2. MATERIALS AND METHODS

2.1 Literature review

During recent decades, climate change has significantly impacted extreme weather events, such as floods, droughts and hurricanes (Lopez-Cantu et al. 2020). As the temperature rises, atmospheric water vapor increases, leading to extreme rainfall events. The frequency of these events is increasing and is becoming unpredictable (Ghasemi et al. 2021). Evaluating the probability of occurrence of these events is crucial for designing sustainable water structures and preventing loss in human lives

Milly et al. (2008, 2015) stated that the assumption of stationarity may no longer be valid. Recently, many studies conducted in Turkey have increasingly questioned the hypothesis of stationarity in hydrological variables. For example, Zaifoğlu (2023) used non-stationary models for frequency analysis of hydrological data in the North Cyprus Basins. Aziz and Yücel (2020) emphasized that the frequency and return levels of hydrological variables cannot be considered stationary due to climate changes and other anthropogenic interventions.

Wi et al. (2016) conducted an analysis utilizing rainfall data from 65 meteorological stations across South Korea, considering durations of 1, 6, 12, and 24 hours. In their study, both Generalized Extreme Value (GEV) and Generalized Pareto Distribution (GPD) models were applied to the time series of rainfall data, incorporating both stationary and non-stationary assumptions for the model parameters. The comparative analysis between these models revealed that return levels of precipitation derived from non-stationary models were consistently higher than those obtained from stationary models applied to the same dataset. This finding indicates that relying solely on stationary models for design purposes may lead to significant inaccuracies.

In their study examining the non-stationary behaviour of extreme flood events, Gül et al. (2014) demonstrated that non-stationarity becomes increasingly pronounced with longer durations in flood data. Utilizing the GEV-CDN method for non-stationary frequency analysis, the study found that the model in which the location parameter varied over time exhibited the highest performance in capturing the non-stationary characteristics of the data.

Oruç (2021) conducted a non-stationary frequency analysis using maximum rainfall data with durations of 5, 10, 15, and 30 minutes, as well as 1, 3, 6, and 24 hours, collected from 17 stations in the Black Sea Region. In this study, the non-stationary GEV distribution was employed, with the location and shape parameters modeled as time-varying, while the scale parameter remained constant. Rainfall data were fitted to GEV distributions under both stationary and non-stationary assumptions, and model performance was assessed using the Negative Log Likelihood (NLL). The findings indicated that GEV models with non-stationary parameters provided a better representation of the observed data according to model adequacy tests.

These studies indicate that since non-stationary behaviour is likely to be observed in extreme rainfall events, it would be more appropriate to model, precipitation data considering non-stationary conditions.

2.2 Data

In this study, time series of observed annual maximum precipitation data for standard durations (t = 5, 10, 15, 30 minutes, and 1, 2, 3, 4, 5, 6, 8, 12, 18, 24 hours) were analysed, using data collected from eight central meteorological stations located in the Aegean Province, as summarized in Table 1. The geographical positions of these stations within the region were mapped using ArcGIS, as illustrated in Figure 1.

Table 1. Directorate general for state hydraulic works and state meteorological stations.

Station No	Station Name	Observation Periods (Years)	Average Annual Precipitation (mm/year)
17155	Kütahya	1941-2010	563.6
17186	Manisa	1958-2010	747.3
17188	Uşak	1941-2010	557.6
17220	İzmir	1938-2010	713.8
17234	Aydın	1959-2010	661.7
17237	Denizli	1959-2010	568.7
17292	Muğla	1944-2010	1209.1
18433	Balıkesir	1957-2010	599.4

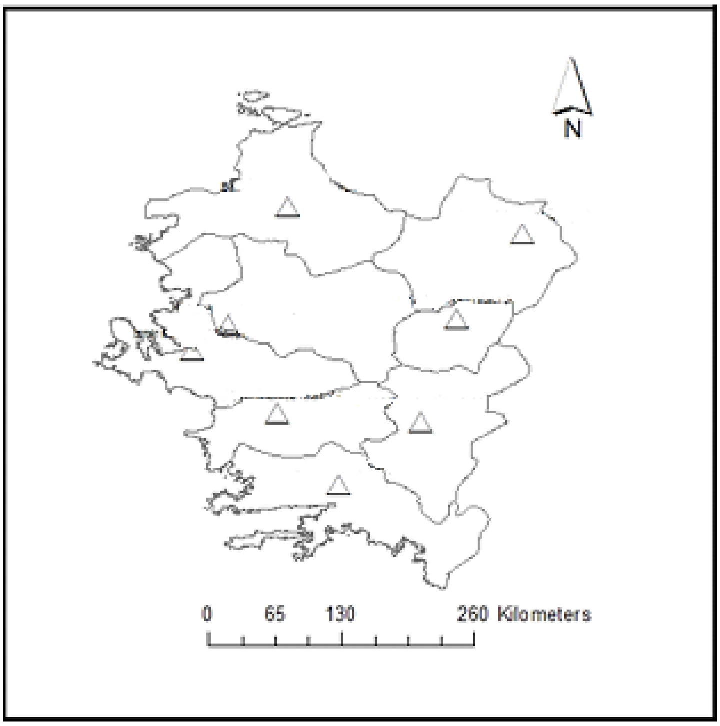

Figure 1. Central meteorological stations in the Aegean Region.

2.3 Methods

Initially, the time series of observed annual maximum precipitation data for standard durations (t = 5, 10, 15, 30 minutes, and 1, 2, 3, 4, 5, 6, 8, 12, 18, 24 hours), collected from eight central meteorological stations in the Aegean Province, were analysed using both parametric and non-parametric trend tests, specifically The Student-T, Mann-Kendall and Spearman's Rho tests. Subsequently, Generalized Extreme Value (GEV) distributions, including stationary GEV and non-stationary GEV1, GEV2, and GEV3, were fitted to the entire dataset. Model selection was guided by examining the Akaike Information Criterion (AIC) and Bayesian Information Criterion (BIC) values for each distribution, ensuring the most appropriate models were chosen. Return levels were then estimated for each station and each period, followed by a comparative analysis between stationary and non-stationary models. The flowchart in Figure 2 outlines the methods implemented in this study.

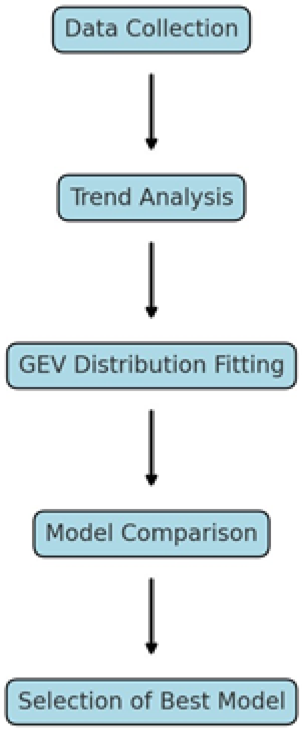

Figure 2. Flowchart of the study methodology.

2.3.1 Trend Analysis

Parametric trend tests can produce more reliable results for detecting the trends in variables fitting the normal distribution compared to non-parametric tests. But, hydro-meteorological data usually show a tendency to not to comply with the normal distribution (Onyutha, 2016).In a study conducted by Önöz and Bayazıt (2003) on trend analysis, The analysis indicated that when the hydrological process under investigation conforms to a normal distribution, the Student-t test performs better in trend detection compared to the Mann-Kendall test. However, it is observed that the performance of parametric tests decreases as the skewness coefficient of the data increases. In cases where the distribution skewness is low, the Student-t test performs as well as the Mann-Kendall test. In the same study, it is stated that non-parametric tests perform better than parametric tests in trend detection regardless of the distribution type when the data are homogeneous.

In a study conducted by Yue et al. (2002) it was established that the Mann-Kendall and Spearman's Rho tests yield nearly identical results in trend analysis, indicating that using both methods together is not necessary. Furthermore, the study demonstrated that the performance of the Mann-Kendall test in trend detection varies dramatically depending on the probability distribution of the process under investigation. According to the study results, the Mann-Kendall test performs best in EV type3 distribution while exhibiting the lowest performance in Lognormal-2 distribution..

A study by Wang et al. (2020) indicates that the performance of the Mann-Kendall test decreases especially when the data size is small and/or the variance is large.

Given the different findings regarding the performance of trend tests, both the parametric Student-t test and the non-parametric Spearman's Rho trend test were utilized in this study, although it was expected that they would yield very similar results to the Mann-Kendall test. The comparison of the performance of trend tests in both trending and non-trending precipitation data is discussed in the findings section.

2.3.2 Frequency analysis and distribution functions

Frequency analysis is a method used to examine the occurrence rates of hydro-meteorological events. This type of analysis can be performed using either graphical techniques, such as frequency histograms and polygons, or analytical approaches. In the analytical methods, probability distribution functions are first fitted to observed precipitation data to model the underlying patterns. Subsequently, the parameters of these distribution functions are estimated. In the present study, the Generalized Extreme Value (GEV) distribution, commonly utilized for modelling extreme values, has been employed, as the analysis focuses on annual maximum precipitation.

The Generalized Extreme Value (GEV) distribution is a generalized mathematical expression that encompasses the first, second, and third forms of the Gumbel distribution. The probability distribution function of the GEV distribution is as shown in Equation 1:

$$F(x) = \exp\left\{-\left[1-\frac{\kappa(x-\xi)}{\alpha}\right]^{1/\xi}\right\} \tag{1}$$

The probability mass function given in Equation 1 expresses ξ as the location parameter, α as the scale parameter, and κ as the shape parameter determining the distribution type. When $\kappa = 0$, the GEV distribution transforms into the Gumbel distribution. When $|\kappa| < 0.3$, the shape of the GEV distribution resembles of the Gumbel distribution. When $\kappa > 0$, the distribution has an upper bound expressed by $\xi + \alpha / \kappa$ and conforms to the type 3 extreme value (EV) distribution. For $\kappa < 0$, the distribution's density function has a right-skewed tail and conforms to the type 2 EV distribution.

The parameter models for the stationary and non-stationary GEV distributions utilized in the study are shown in Table 2.

Table 2. GEV Models.

Models	**Parameters**		
GEV	α=constant	ξ=constant	κ=constant
GEV1	$\alpha(t)= \alpha_0+\alpha_1 t$	ξ=constant	κ=constant
GEV2	α=constant	$\xi(t)= \xi_0+\xi_1 t$	κ=constant
GEV3	$\alpha(t)= \alpha_0+\alpha_1 t$	$\xi(t)= \xi_0+\xi_1 t$	κ=constant

2.3.3 Selecting the best model

The selection and validity of the model that most accurately represents hydro-meteorological time series data have a substantial influence on the reliability of future event predictions. Consequently, conducting goodness-of-fit tests is essential to identify the most appropriate model from those proposed. In this study, the Akaike Information Criterion (AIC) and Bayesian Information Criterion (BIC) were employed to guide the selection of the model that best represents the data and provides the most realistic future forecasts. Although both AIC and BIC are used to assess model selection, AIC evaluates the goodness of fit of an estimated statistical model, whereas BIC is a measure of model complexity, particularly for parametric models with varying numbers of parameters. In model comparison, the model that produces the lowest AIC and BIC values is consistently preferred.

Akaike Information Criterion, the maximized log-likelihood function of the model ($\hat{\theta}$), and k denotes the number of independent parameters in the model, is represented in Equation 2:

$$AIC = -2Log\,(\hat{\theta}) + 2k \tag{2}$$

Bayesian Information Criterion, $L(\hat{\theta})$ denotes the value evaluated at the logarithmic maximum likelihood estimate of the candidate model, k indicates the number of estimated parameters in the candidate model, and n is the sample size, as shown in Equation 3:

$$BIC=-2\times \log L(\hat{\theta})+k\times \log(n) \tag{3}$$

3. RESULTS AND DISCUSSION

The results of trend tests conducted on rainfall data obtained from meteorological stations within the scope of the study, as well as the most suitable models selected according to AIC and BIC values, are summarized in Tables 3 and 4.

Table 3. Best Models for trend observed precipitation periods.

Station Name	Precipitation periods with trend	Student T	Mann-Kendall	Spearman's Rho	Best Model
Aydın	30 Minutes to 12 hours	Increasing trend	Increasing trend	Increasing trend	GEV3
Balıkesir	5 Minutes	Decreasing trend	Decreasin g trend	Decreasing trend	GEV2
İzmir	30 Minutes to 24 hours	Increasing trend	Increasing trend	Increasing trend	GEV3
Kütahya	12 hours to 18 hours	Decreasing trend	Decreasin g trend	Decreasing trend	GEV3
Manisa	24 hours	Decreasing trend	No trend	Decreasing trend	GEV
Muğla	8 to 18 hours	Decreasing trend	Decreasin g trend	Decreasing trend	GEV3

Table 4. Best Models for precipitation periods without trend.

Station Name	Precipitation periods with no trend	Student T	Mann-Kendall	Spearman's Rho	Best Model
Aydın	5 to 15 Minutes + 24 hours	No trend	No trend	No trend	GEV
Balıkesir	10 Minutes to 24 hours	No trend	No trend	No trend	GEV
Denizli	5 Minutes to 24 Hours	No trend	No trend	No trend	GEV
İzmir	5 to 15 Minutes	No trend	No trend	No trend	GEV
Kütahya	5 minutes to 8 hours +24 hours	No trend	No trend	No trend	GEV
Manisa	5 Minutes to 18 hours	No trend	No trend	No trend	GEV
Muğla	24 hours	No trend	No trend	No trend	GEV
Uşak	8 to 18 hours	No trend	No trend	No trend	GEV

Although various researchers have noted that the performance of the Student's t-test may decline due to its assumption of normal distribution (e.g., Wilks, 2011; Yue et al., 2002), the results of this study show consistency across different statistical methods. As demonstrated in Tables 3 and 4, the findings from the Student's t-test align closely with those of the non-parametric Mann-Kendall and Spearman's Rho tests, with the exception of the 24-hour precipitation data for Manisa. These results are in line with previous study (e.g. Şen, 2017), which suggests that non-parametric tests like Mann-Kendall are often more robust for detecting trends in hydro-meteorological data, as they do not rely on normal distribution assumptions.

For the 24-hour precipitation data in Manisa, both the parametric Student's t-test and the non-parametric Spearman's Rho test indicate a decreasing trend, while the Mann-Kendall test reveals no significant trend. This discrepancy highlights the sensitivity of different tests to distribution assumptions, as also noted by Burn and Elnur (2002), who found that parametric tests can sometimes suggest trends where non-parametric tests do not. However, when the results from Table 4 are considered—showing that the Generalized Extreme Value (GEV) distribution is the most appropriate model for this dataset—it suggests that the conclusion drawn by the Mann-Kendall test, which indicates no significant trend, should be favored. Similar conclusions have been drawn in studies by Koutsoyiannis (2004) and Katz et al. (2002), where GEV distributions were found to better capture extreme precipitation events, reinforcing the importance of selecting the correct distribution model when assessing trends.

For precipitation periods where a trend is observed, models constructed with non-stationary parameters are identified as representing the most suitable distributions, as indicated by both the Akaike Information Criterion (AIC) and Bayesian Information Criterion (BIC). The GEV2 and GEV3 models specifically were found to perform best, aligning with findings from other studies (Coles et al. 2001; Katz et al., 2002), which have shown that GEV distributions with non-stationary parameters are effective for modelling extreme values in precipitation data. This suggests that the use of non-stationary GEV distributions with two or three parameters would be appropriate in the design phase for precipitation periods exhibiting trends, a recommendation also supported by Katz and Brown (1992).

As shown in Table 4, for precipitation periods where no trend is detected, the use of standard GEV distributions with stationary parameters proves more effective in representing the hydrological process. This finding is consistent with research by Hosking and Wallis (1997), who found that stationary GEV models better capture the behaviour of hydrological data without significant trends. Thus, conducting trend analyses for hydro-meteorological processes before advancing to the design phase is of paramount importance, as emphasized by studies like Burn and Elnur (2002) and Şen (2017), which argue for the necessity of comprehensive trend detection before the application of hydrological models.

By integrating the results of this study with those from previous research, it becomes clear that the choice of statistical tests and distribution models has a significant impact on the interpretation of trends in hydro-meteorological data, and that non-parametric methods combined with appropriate distribution models offer a more reliable approach for such analyses.

4. CONCLUSION AND RECOMMENDATIONS

In this study, precipitation processes under non-stationary conditions, driven by projected climate change, were modelled using various probability distribution functions. Trend tests were applied to the annual maximum precipitation data. Regardless of the trend test outcomes, both stationary and non-stationary Generalized Extreme Value (GEV) distributions were fitted to the data from different time periods across various stations. The GEV distribution parameters, goodness-of-fit metrics, and expected return levels for different return periods were calculated using the exTremes and ismev packages in the R Studio open-source software. The results indicated that non-stationary distributions are more appropriate for modelling precipitation periods exhibiting trends.

Based on the findings of this study, different cities exhibit varying trends in precipitation patterns, and appropriate statistical models must be employed to accurately capture these behaviours. The following conclusions and recommendations are made:

For Aydin station, precipitation durations of 5, 10, 15 minutes, and 24 hours, have shown no significant trends. Therefore, the use of a stationary Generalized Extreme Value (GEV) distribution is recommended. For 30-minute and 1- to 12-hour precipitation, an increasing trend was observed, suggesting that the non-stationary GEV3 distribution is more appropriate for capturing these changes.

For Balıkesir station, a decreasing trend was identified for 5-minute precipitation, for which the non-stationary GEV2 distribution is recommended. For all other time intervals, where no trend was observed, the stationary GEV model is deemed suitable.

For Denizli station, since no trends were observed for any of the precipitation durations, the stationary GEV distribution is appropriate across all time intervals.

For Izmir station, 5, 10, and 15-minute precipitations have shown no significant trends, making the stationary GEV model suitable. However, for 30-minute and 1- to 24-hour precipitation, an increasing trend was observed, necessitating the use of the non-stationary GEV3 distribution.

For Kütahya station, a decreasing trend was identified for 12- to 18-hour precipitation durations, where the non-stationary GEV3 distribution should be applied. For all other intervals with no observable trends, the stationary GEV model is recommended.

For Manisa station, no trends were observed for any precipitation durations, thus the stationary GEV distribution is appropriate for all time intervals.

For Muğla station, 8- to 18-hour precipitations have shown a decreasing trend, and the non-stationary GEV3 distribution is recommended. For other durations, the stationary GEV model is suitable, as no significant trends were found.

For Uşak station, no observable trends were detected for any precipitation periods, so the stationary GEV distribution can be employed across all time intervals.

In cities like Aydın and İzmir, where increasing trends were observed, especially in short-duration and high-intensity precipitation events, flood risks may be underestimated if stationary models are used. It is therefore essential to consider non-stationary return levels in flood modelling to more accurately assess future risks. A review of current flood risk management strategies using non-stationary frequency analyses is strongly recommended for these regions.

In regions such as Muğla and Kütahya, where decreasing trends were identified, particularly for longer-duration precipitation, a more comprehensive investigation into the implications of these trends on agriculture and water resources is necessary. These decreasing trends may indicate a heightened risk of meteorological drought, which could adversely impact agricultural productivity and water availability. Therefore, targeted studies focusing on drought risk and long-term water resource management are advised for these areas.

In summary, this study underscores the importance of using both stationary and non-stationary models depending on the trends identified in regional precipitation data. Future risk assessments, particularly in hydrological and agricultural planning, should account for these variations to ensure effective resource management and disaster preparedness.

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