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RESEARCH ARTICLE - HYDROLOGY

Trend and nonstationary relation of extreme rainfall: Central Anatolia, Turkey

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Abstract
The frequency of extreme rainfall occurrence is expected to increase in the future and neglecting these changes will result in the underestimation of extreme events. Nonstationary extreme value modelling is one of the ways to incorporate changing conditions into analyses. Although the definition of nonstationary is still debated, the existence of nonstationarity is determined by the presence of significant monotonic upward or downward trends and/or shifts in the mean or variance. On the other hand, trend tests may not be a sign of nonstationarity and a lack of significant trend cannot be accepted as time series being stationary. Thus, this study investigated the relation between trend and nonstationarity for 5, 10, 15, and 30 min and 1, 3, 6, and 24 h annual maximum rainfall series at 13 stations in Central Anatolia, Turkey. Trend tests such as Mann–Kendall (MK), Cox–Stuart (CS), and Pettitt's (P) tests were applied and nonstationary generalized extreme value models were generated. MK test and CS test results showed that 33% and 27% of 104 time series indicate a significant trend (with $p<0.01$–$p<0.05$–$p<0.1$ significance level), respectively. Moreover, 43% of time series have outperformed nonstationary (NST) models that used time as covariate. Among five different time-variant nonstationary models, the model with a location parameter as a linear function of time and the model with a location and scale parameter as a linear function of time performed better. Considering the rainfall series with a significant trend, increasing trend power may increase how well fitted nonstationary models are. However, it is not necessary to have a significant trend to obtain outperforming nonstationary models. This study supported that it is not necessarily time series to have a trend to perform better nonstationary models and acceptance of nonstationarity solely depending on the presence of trend may be misleading.

Keywords Nonstationary · Mann–Kendall · Cox–Stuart · Pettitt's test · Trend · Generalized extreme value

Introduction

Changing precipitation patterns arise as a result of climate change (Putnam and Broecker 2017). Under changing conditions, extreme precipitation events are expected by the end of the 21st century (Willems et al. 2012; IPCC 2013; Liew et al. 2014; Pohl et al. 2017). The frequency and severity of extreme rainfall are expected to increase (Ren et al. 2019) and neglecting the changing frequency may cause underestimation of extreme events (Cheng and Aghakouchak 2014). Fernandez and Peek (2020) noted the direct impacts of climate change at a city level, such as water-resource availability or extreme event-induced stress on urban infrastructure and Sarhadi et al. (2017) show that a stationary approach in frequency analyses may underestimate the magnitude (return level) of extreme precipitation events, and updated design assumptions must be presented in these changing conditions. Faulkner et al. (2019) recommend that nonstationary analyses should be conducted as well as traditional methods when a pronounced trend is determined. For this reason, researchers have tried to develop alternatives to stationary assumption of observed data and have investigated incorporating nonstationary characteristics into extreme value modelling (Wi et al. 2016).

Although the definition of nonstationary is still debated, the existence of nonstationarity is determined by the presence of significant monotonic upward or downward trends

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and/or shifts in the mean or variance (Cheng et al. 2015; Razavi et al. 2015; Ren et al. 2019). Trend tests, particularly the Mann–Kendall (MK) test, are used to determine nonstationary behavior in many studies (Cheng and AghaKouchak 2014; Wi et al. 2016; Šraj et al. 2016; Ren et al. 2019; Tian et al. 2020). On the other hand, trend tests may not be a sign of nonstationarity (Serinaldi et al. 2018) or lack of significant trend detection cannot be accepted as time series are stationary but rather simply further analyses may be needed. Panthou et al. (2012) also note that, although stationary test results may be positive for a certain time series, this is not necessarily valid over a longer period.

Rainfall and extreme rainfall have been examined in various studies for near regions and in Turkey. For instance, Giorgi (2006) developed a regional climate change index and investigated different parts of the world. The results of this index represent that in the Mediterranean region climate change will have a critical role on the future of total precipitation. Burić and Doderović (2020) investigated Montenegro-Podgorica for several precipitation and temperature indices. Their results showed that the climate of Podgorica is getting more arid and face more extreme events since the number of days with significantly decreased while total annual and seasonal precipitation did not exhibit a significant change. Moreover, Mostafa et al. (2019) studied 8 representative stations for Egyptian climate and revealed no significant change over the observed period for precipitation. On the other hand, their results predicted a general decrease in total precipitation based on the future projection results over the North of Egypt. Öztürk et al. (2017) indicated that future precipitation over Turkey is expected to decrease, and Turkes et al. (2020) stated that, according to RCM results for almost all parts of Turkey, a strong decrease in precipitation and a more arid period are expected considering 2021–2050 with reference to 1971–2000. These results are also supported by Lange (2019) and Demircan et al. (2017), which noted a decreasing amount of rainfall in inner parts of the Anatolian region. According to Sen et al. (2012), the Central Anatolia Region is expected to experience a significant decrease in precipitation in winter and more severe drought conditions. Extreme rainfall was also investigated by researchers: Sensoy et al. (2013) investigated the extreme climate indices in Turkey for about 109 stations and for the period from 1960 to 2010. Except Aegean and Southeastern Anatolia regions, heavy precipitation days increase in most of the stations. Furthermore, in most of the stations, a maximum 1-day precipitation followed an increasing trend, apart from Southeastern Anatolia. On the other hand, Abbasnia and Toros (2020) examined the extreme temperature and precipitation indices for 71 stations across Turkey and their results show that stations located in inland Central Anatolia have decreased in very heavy and extremely heavy rainfall.

Most of the studies that attempt to explore the variability of precipitation focus on yearly total, monthly, or daily scale. However, daily temporal resolution data are not well suited to extreme value analysis; for instance, urban flash flooding occurs over short durations, such as in a few minutes to hours, or hydrological infrastructure and facility design uses sub-daily and sub-hourly storm durations as design parameters. Therefore, it is essential to analyze extreme rainfall for shorter durations, such as sub-daily or sub-hourly. Furthermore, the nonstationarity and trend relationship was not a subject of interest for most of these studies.

Although rainfall events are random processes, potential behavior and characteristics can be estimated with long enough and good-quality data. The main goal of this study is to investigate the trend and nonstationary relation for 5–10–15–30 min and 1–3–6–24–h annual maximum rainfall series at 13 central stations in Central Anatolia and examine the relationship between nonstationary models and trend tests. The reason Central Anatolia was chosen is that the region is sensitive to climate change impacts, second largest in terms of area and population, and comprises important agricultural basins and major cities, including Ankara, the capital city. In this paper, the MK trend test (Mann 1945, Kendall 1975, Gilbert 1987), Cox–Stuart test (Cox and Stuart 1955), and Pettitt's test (Pettitt 1979) were applied to annual maximum rainfall series with a minimum data length of 49 years and the results were compared for 13 stations in Central Anatolia. Also, nonstationary generalized extreme value (GEV) models for which the location and/or scale parameters of distribution vary as a linear function of time were constructed and used to identify nonstationary tendencies of rainfall series. Nonstationary model performance was compared according to Akaike Information Criterion (AIC) and Bayesian Information Criterion (BIC) values. Trend results were then compared to nonstationary models to investigate their potential relationship.

This paper is organized as follows. "Materials and methods" section introduces the study area, station list, data source, and reviews the methodology, in particular the Mann–Kendall trend test, Cox–Stuart test, and Pettitt's test, for trend detection and GEV stationary and nonstationary model construction and performance criteria. "Results and discussion" section reveals the results of trend detection, stationary and nonstationary models, and their relationship. "Conclusions and remarks" section provides a discussion and final remarks.

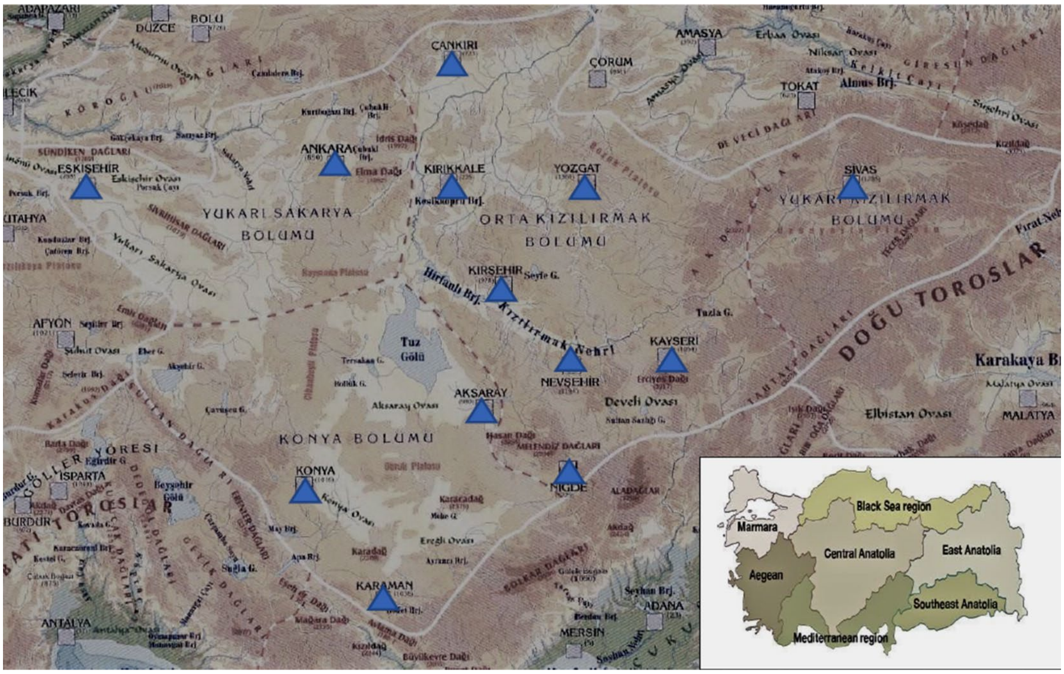

Fig. 1 Map of the selected stations in the study area

Materials and methods

Study area and data

Central Anatolia is one of the seven geographical regions in Turkey. It is located in the center of the country (Fig. 1). Central Anatolia is approximately 20% of the whole area of Turkey and covers the 13 provinces of Turkey (Aksaray, Ankara, Cankiri, Eskisehir, Karaman, Kayseri, Kirikkale, Kirsehir, Konya, Nevsehir, Nigde, Sivas, and Yozgat).

The Central Anatolian Region land cover originates from different forms; dry, arid highlands of Anatolia which extend to the east, lie between the Taurus and the Northern Anatolian mountain ranges (Apaydin et al. 2011).

In Central Anatolia, most parts of the region are classified as semi-dry and semi-dry-less humid. The difference between day and night temperature is high. The Taurus Mountains lie in the south and the Pontic Mountains in the north. Elevation of the region increases toward east and the average altitude of the region is over 1000 m. For this reason, mild weather cannot pass the surrounding mountains, so continentality effects are dominant in the region. Spring and winter are the rainiest seasons, and rain type is convectional and frontal.

The annual maximum rainfall series of 13 stations were obtained from the Turkish State Meteorological Service (TSMS). Table 1 shows the stations used in this study.

Table 1 Selected 13 stations in Central Anatolia

Station	Lon	Lat	Elevation (m)	Data range
Aksaray	33.99	38.36	965	1966–2015
Ankara	32.86	39.97	891	1950–2015
Cankiri	33.61	40.6	751	1960–2015
Eskisehir	30.55	39.76	801	1957–2012
Karaman	33.22	37.19	1025	1966–2015
Kayseri	35.5	38.68	1093	1956–2015
Kirikkale	33.51	39.84	751	1967–2015
Kirsehir	34.15	39.16	1007	1942–2015
Konya	32.55	37.96	1031	1950–2015
Nevsehir	34.7	38.6	1260	1966–2015
Nigde	34.67	37.95	1211	1960–2015
Sivas	37	39.74	1285	1958–2015
Yozgat	34.8	39.82	1298	1960–2015

Methods

This study conducted statistical analyses of the annual maximum rainfall data using the following tools:

- Mann–Kendall trend test to evaluate the annual maximum trend features- statistical significance of the rainfall time series.
- Cox–Stuart trend test to evaluate the annual maximum trend features of the rainfall time series.

- Pettitt's test to evaluate the potential change point of the rainfall time series.
- Stationary and nonstationary GEV model performance results of rainfall series.

Synthesis of methods was used to evaluate rainfall time series' trend for nonstationarity and is described in the following sections. R package extRemes (Gilleland and Katz 2016; Gilleland 2020) was used for GEV model construction. R package trend (Pohlert 2020) was used for the trend tests.

Trend and change point tests

The statistical tools that provide trend tests are generally divided into two fundamental groups: parametric and nonparametric. It is generally thought that using nonparametric tests is more appropriate to conducting trend analysis for non-normally distributed hydrometeorological time series data (Yilmaz and Perera 2014; Ledvinka 2014; Bayazit 2015).

The MK trend test (Mann 1945; Kendall 1975; Gilbert 1987) is one of the nonparametric trend tests for trend detection and was used in this study to detect whether there is a monotonic upward or downward trend over time for precipitation. MK test is a rank-based test and has many trend detection applications with hydrometeorological time series (Yilmaz and Perera 2014; Cheng and AghaKouchak 2014; Yucel et al. 2014; Onyutha et al. 2016).

The nonparametric Cox–Stuart trend test (Cox and Stuart 1955; Conover 1999) tests is considered to be less powerful than the MK test (Ledvinka 2014; Rutkowska 2015; Militino et al. 2020). On the other hand, it is said to be very robust for trend analyses (Steinke et al. 2020).

The Cox–Stuart test belongs nonparametric tests group. H: No monotonic trend exists in the series, H_A: The series is characterized by a monotonic trend, are the hypothesis tested for the trend existence of the series.

Let $z_1,\ldots, z_k$ be a series of data. When k is even (middle value is not considered if k is not even) the series divided into two parts: $z_1,\ldots,z_{\frac{k}{2}}$ and $z_{\frac{k+2}{2}}, \ldots, z_k$. Then, the pairs ($z_j$, $z_{j+\frac{k}{2}}$) are considered for $j=1,\ldots, \frac{k}{2}$. The number of pairs in which $z_j < z_{j+\frac{k}{2}}$ is then become the test statistic (Rutkowska 2015; Steinke et al. 2020; Chen and Huang 2020).

Any significant change points for the time series were also investigated. Change points in a rainfall time series might occur because of climate change, anthropogenic-induced changes, recording error or methodology switch, or using different equipment. It is also possible to detect a change point visually in a time series from figures or graphs; on the other hand, statistical determination is vital for solid results.

In this study, Pettitt's change point test was also employed (Pettitt 1979).

Pettitt's test is a nonparametric approach. The test statistic is calculated by using the ranks $r1$, $r2$, …, rn ranks of the series $X1$, $X2$, …,Xn

$$Y_k = 2\sum_{i=1}^{k} r_i - k(n+1)$$

where $k=1, 2, \ldots, n$.

The statistic reaches maximum or minimum at year $k=K$ in case of a change point or break at year K (Militino et al. 2020; Patakamuri et al. 2020)

Stationary and nonstationary models

Extreme value analysis (EVA) is commonly used for investigating meteorological extremes (Scotto et al. 2011; Cheng et al. 2015; Vahedifard et al. 2017; Makkonen and Tikanmaki Makkonen and Tikanmäki 2019). Extreme value theory (EVT) is concerned with the statistical properties of the tails of distributions and provides the necessary methods to estimate the distribution of the extremes of a time series (Umbricht et al. 2013).

Extreme value theory uses probabilistic distribution functions such as GEV or generalized logistic (GL) function to annual (block) maximum (A(B)M) series or generalized Pareto distribution (GPD) function which is fitted on a peak-over-threshold (POT) series (Collet et al. 2017). It has a broad application field in engineering applications that deal with extreme conditions (Coles and Sparks 2006).

The GEV distribution function is accepted as being capable of fitting the block maxima (BM) (maximum of long blocks of data, such as annual maximum values of daily precipitation height) of data (Gilleland and Katz 2016). The GEV distribution has three parameters, namely location (μ), scale (σ), and shape (ξ) parameters, and is given by Eq. (1) (Coles and Sparks 2006; Coles 2001);

$$G(z) = \exp\left[-\left\{1 + \xi\left(\frac{z-\mu}{\sigma}\right)\right\}_+^{-1/z}\right], \tag{1}$$

where $z_+ = \max\{z, 0\}$, $\sigma > 0$, and $-\infty < \mu$, $\xi < \infty$ (Coles 2001).

Equation (1) covers three types of df's depending on the sign of the shape parameter, ξ. Fréchet distribution results from $\xi > 0$, Weibull distribution when $\xi < 0$, and Gumbel distribution results from taking the limit as $\xi \rightarrow 0$ (Gilleland and Katz 2016). Maximum likelihood estimation (MLE) was the preferred method for parameter estimation of models in this study.

The BM approach aims to describe the probability distribution of the maxima of a block. In the BM approach, equal length of blocks are selected and maximum values from each block are determined, and subsequently the GEV distribution is fitted to the obtained maxima series to estimate the exceedance probability (p), and calculate the return period ($1/p$) and its return level (zp). The size of the block is important because the distribution of the maximum series of the parent distribution may not converge to the GEV distribution as expected for the BM approach because of a small number of blocks and block size-caused biases and errors (Wang et al. 2016; Cai and Hames 2010; Umbricht et al. 2013).

For this study, stationary and nonstationary GEV models with a BM approach were constructed and distribution parameters were estimated using MLE. Yilmaz and Perera (2014) indicate that maximum likelihood estimation (MLE) method is a preferred method for parameter estimation of nonstationary models due to its suitability for incorporating nonstationarity into the distribution parameters as covariates. According to Roslan et al. (2020), MLE is adaptable for model changes and mostly chosen to estimate the parameters of GEV distribution because of its advantageous asymptotic properties. Moreover, MLE can be used for nonstationary models, models with temporal or other effects (Roslan et al. 2020). In this method, model parameters were selected as they maximize the likelihood function which enables to obtain a distribution that characterize the observed data in the best way (Mahmoodian 2018).

To obtain nonstationary models, distribution parameters were set to be a function of covariates such as time and temperature, and for every value of covariate, a unique return level value was calculated. Different combinations for nonstationary cases were tested and compared to find out the best-fitted model among stationary and nonstationary models. In the present study, all model parameters were set to constant for the stationary case, and location and/or scale parameters were assumed to be a function of time for the nonstationary case. The nonstationary models that describe each of these cases with their developed parameters are presented in Table 2.

Superiority of nonstationary models to stationary models and among themselves was inspected by AIC, BIC, and negative log-likelihood (NLL). Both AIC and BIC are capable of model selection and were designed to be used with MLE

Table 2 Nonstationary models with time-dependent location and scale parameters

Model	Location	Scale	Shape
NST1	$\mu t=\beta 0+\beta 1t$	$\sigma t=\beta 0+\beta 1t$ (log-link)	ξ (constant)
NST2	$\mu t=\beta 0+\beta 1t$	$\sigma t=\beta 0+\beta 1t$	ξ (constant)
NST3	$\mu t=\beta 0+\beta 1t$	σ (constant)	ξ (constant)
NST4	μ (constant)	$\sigma t = \beta 0+\beta 1t$ (log-link)	ξ (constant)
NST5	μ (constant)	$\sigma t = \beta 0 + \beta 1t$	ξ (constant)

which is the parameter estimation method in this study; AIC is good at finding appropriate predictive models, BIC which is said to be good for small sets of well-justified models was developed for the purpose of model averaging (Wang and Liu 2006; Hooten and Hobbs 2015).

Similar to ordinary least squares, the negative of the log-likelihood is used to determine the most likely value of the parameter that is actually the value which makes the negative log-likelihood approach its minimum; thus, the maximum likelihood estimate is equal to the minimum negative log-likelihood estimate (McGarigal 2017).

Results and discussion

The MK trend test, Cox–Stuart test, and Pettitt's test were applied for different durations of rainfall time series recorded at various locations in Central Anatolia. Figure 1 provides the meteorological sites used in this study. Trend analysis was performed through the abovementioned tests, and results were compared.

Moreover, 5 nonstationary models were constructed and applied for 5–10–15–30 min and 1–3–6–24 h rainfall series. Besides, stationary models also performed for the corresponding rainfall durations. First, performance of nonstationary models was compared with stationary models in terms of AIC and BIC to investigate model superiority. Nonstationary models that outperformed stationary models were compared with trend test results at all stations for every annual maximum rainfall series with a minimum data range of 49 years.

Table 3 shows the results obtained by means of the MK test, CS test, Pettitt's test and nonstationary/stationary model comparison at each station. Critical values at different significance levels were used to determine the presence of statistically significant trends. In Table 4, also number of significant trends with 0.01 (***), 0.05 (**), 0.1 (*), insignificant (o), and outperformed nonstationary model existence ($\surd$) can be seen.

Based on the MK test statistics, significant results were detected, with annual maximum rainfall of Aksaray, Ankara, Çankırı, Eskişehir, Kayseri, Kırşehir, Konya, Niğde, and Yozgat at different significant levels. No significant trend was detected at Karaman, Kırıkkale, and Sivas stations according to MK test.

CS test results were consistent with MK test results; however, the presence of a significant trend decreased. For instance, Aksaray station 3 h series, Çankırı station 5 min series Eskişehir station 5 min series, Kayseri station 5 min and 3 h series, Niğde station 15 min and 3 h series, and Yozgat station 30 min data were trendless for 0.01–0.05 and 0.1 significance levels.

Table 3 The results of the Mann–Kendall trend test, Cox–Stuart test, Pettitt's test, and nonstationary model performance for 5–10–15–30 min and 1–3–6–24 h annual maximum rainfall series

	Aksaray				Ankara				Çankırı				Eskişehir			
	MK	CS	*P*	NST	MK	CS	*P*	NST	MK	CS	*P*	NST	MK	CS	*P*	NST
5 min	o	o	o	o	***	**	**	√	*	o	o	√	*	o	o	√
10 min	o	o	o	o	**	*	*	√	o	o	o	o	*	*	*	o
15 min	o	o	o	o	*	**	*	o	o	o	o	o	*	***	*	√
30 min	o	o	o	o	*	**	*	o	o	o	o	o	o	**	o	o
1 h	o	o	o	o	**	*	**	√	o	o	o	o	o	o	o	o
3 h	**	o	**	√	o	o	o	o	o	*	o	√	o	o	o	o
6 h	o	o	o	√	o	o	o	o	*	**	**	√	o	o	o	o
24 h	o	o	o	o	o	o	o	√	o	o	o	√	o	o	o	√

	Karaman				Kayseri				Kırıkkale				Kırşehir			
	MK	CS	*P*	NST	MK	CS	*P*	NST	MK	CS	*P*	NST	MK	CS	*P*	NST
5 min	o	o	o	o	*	o	*	√	o	o	o	o	o	o	o	o
10 min	o	o	o	o	*	*	*	√	o	o	o	o	o	o	o	√
15 min	o	o	o	o	o	o	o	√	o	o	o	o	*	o	o	√
30 min	o	o	*	o	*	*	*	√	o	o	o	o	***	***	*	√
1 h	o	o	o	o	o	o	o	√	o	o	o	o	***	***	**	√
3 h	o	o	o	o	*	o	o	√	o	o	o	o	***	***	**	√
6 h	o	o	o	o	o	o	o	o	o	o	o	o	***	***	***	√
24 h	o	o	o	o	o	o	o	√	o	o	o	o	***	***	**	√

	Konya				Nevşehir				Niğde				Sivas				Yozgat			
	MK	CS	*P*	NST	MK	CS	*P*	NST	MK	CS	*P*	NST	MK	CS	*P*	NST	MK	CS	*P*	NST
5 min	o	o	o	o	o	o	o	o	o	o	o	o	o	o	o	o	o	o	o	o
10 min	o	o	o	o	o	o	o	o	*	*	o	√	o	o	o	√	o	o	o	o
15 min	o	o	o	o	o	o	o	o	***	o	*	√	o	o	o	√	o	o	o	o
30 min	o	o	o	o	o	o	o	o	***	***	***	√	o	o	o	√	*	o	o	o
1 h	o	o	o	o	o	o	o	o	***	*	***	√	o	o	o	√	**	*	o	√
3 h	o	o	o	o	o	o	o	√	***	o	**	√	o	**	o	o	**	**	o	o
6 h	o	*	o	√	o	o	o	o	***	*	*	√	o	o	o	o	*	**	*	√
24 h	***	***	**	√	o	o	o	o	*	**	o	√	o	o	o	√	o	o	o	√

0.01 (***), 0.05 (**), 0.1 (*), insignificant (o) and better performed NST model existence (√)

Table 4 Number of significant trend and no trend time series

Test	√(Trend)	o(Insignificant)	*	**	***
Mann–Kendall	33	71	16	5	12
Cox–Stuart	28	76	11	9	8
Pettitt's Change Point	25	79	13	9	3
Better Performed Series with NST Models	45	59			

Significance level 0.01 (***), 0.05 (**), 0.1 (*)

Series with a low significant trend according to MK test results were generally trendless according to the CS test, but this was not valid for every series. Although there was a significant trend in both MK and CS results, the MK test results showed higher significance in general. On the other hand, unlike common behavior of the rainfall series, there are rainfall series that showed higher significance for CS test over MK test and showed a trend, although MK test results indicated insignificant, such as Çankırı station 3 h series or Ankara 15 min series. Pettitt's test results show that for any significant change point, interested rainfall series had a significant trend according to MK test, except for one series.

At each station, 5 nonstationary and 1 stationary models were constructed for all rainfall series and were compared in terms of AIC and BIC, as shown in "Appendix" and nonstationary models with better performance over stationary models can be seen from "Appendix". Considering MK test, CS test, and Pettitt's test results, nonstationary model results seem to be the most compatible with MK test results, and 45 of the 104 rainfall series outperformed corresponding stationary models. Although 14 out of 45 nonstationary model rainfall series showed insignificant according to the MK test for all significance levels, only 3 rainfall series with a significant trend did not outperform the nonstationary model, namely Ankara station 15 and 30 min and Eskişehir station 10 min. However, stationary and nonstationary model AIC results of these three series were remarkably close. Although there are other examples, series with higher significance (*p* value smaller than 0.01) performed better in terms of nonstationarity. The difference between stationary and nonstationary model AIC and BIC values increased with the increasing significance (strong trend). However, these differences are not considerable compared to the decreasing trend significance, and only AIC values indicate better performance with these rainfall series.

In Table 4, the number of significant trend and no trend time series is shown. As it is the presence of trend that is important for comparing with nonstationary models, the direction of the significant trends is beyond the scope of this study.

MK test results show a trend for 33 rainfall series, 12 of them with 0.01, 5 of them with 0.05, and 16 of them with 0.1 significance level. CS test shows that 28 of 104 rainfall series have a significant trend and Pettitt's test reveals that 25 of 104 rainfall series have significant change points. The level of significance can be seen in Table 4. Of the 104 time series, 45 performed better in terms of nonstationary models with time used as covariate.

Furthermore, 107 out of 520 (5 models $\times$ 13 stations $\times$ 8 rainfall series) nonstationary models showed lower AIC values and 40 of them showed lower BIC values than their related stationary model. When BIC values are smaller, AIC values of that model are also smaller compared with the stationary model. Moreover, model 3 and model 2 showed the best performance among nonstationary models and these models use time as covariate for location only and for both location and scale, respectively.

Considering the rainfall series with significant trends in this study, increasing trend power may increase the power of time-dependent nonstationary models. However, it is not necessary to have a significant trend to obtain outperforming time-dependent models and accept nonstationary based on trend existence. For instance, Yang et al. (2019) used historical flood data to calculate nonstationary return periods. They figure out that the results change with the accepted definition of nonstationary. MK test results reveal that annual maximum rainfall at Karaman, Kırıkkale, Nevşehir, and Sivas stations were dominated by insignificant trends. These series also did not show a better performance for time-dependent models, except Sivas station. Annual maximum rainfall series at the other stations showed both significant trends and had time-dependent models that performed better than their related stationary models.

Moreover, in this study, only time (year) is used as a covariate, however, it is not necessarily to be the best fit covariate(s) that define the nonstationarity. Agilan and Umamahesh (2017) also emphasized this issue and underlined the importance to identify best covariates to model nonstationarity for extreme rainfall series. There are also studies in Turkey that deal with extreme rainfall conditions and trends, but nonstationary processes are not a subject of interest in many of them. Aziz (2018) used four distributions (GEV, Gumbel, Normal and Lognormal) distributions for yearly and seasonal maximum precipitations and identified both increasing and decreasing impacts of nonstationarity at the Central Anatolia. On the other hand, Yilmaz (2017) studied Antalya and found no evidence of nonstationarity in the region. Haktanır and Çıtakoğlu (2014) investigated standard duration annual maximum rainfall series with various durations and lengths of 14 stations up to 2010 in Turkey to capture the statistical behavior of series and concluded that 90% of all studied annual maximum rainfall series are trendless, independent, stationary, and homogeneous for Turkey.

However, the results of this study indicate a significant trend and nonstationarity. MK test and CS test results show that 33% and 27% of 104 time series indicate significant trends (with 0.01–0.05–0.1 significance level), respectively. Moreover, 43% of time series outperformed time-dependent models. Of the five different time-dependent nonstationary models, two performed better. The model with location parameter as a linear function of time performed best and the model with location and scale parameter as a linear function of time had the second-best performance.

Conclusions and remarks

In this paper, MK trend test, CS test, and Pettitt's test were applied to annual maximum rainfall series with a minimum data length of 49 years, and the results were compared for 13 stations in Central Anatolia. Also, nonstationary GEV models with the location and/or scale parameters of distribution varying as a linear function of time were constructed and used to identify nonstationary tendencies of rainfall series. Nonstationary model performance was compared according to AIC and BIC values. Trend results were then compared to nonstationary models to investigate their potential relationship.

The Mann–Kendall trend test has been used in many studies and is among the most widely used nonparametric trend tests (Nigussie and Altunkaynak 2018, Keggenhoff et al. 2014, Wang et al. 2019, Militino et al. 2020). The Cox–Stuart test is also a nonparametric test and used in trend detection of many hydrological variables (Sen and Niedzielski

2010, Fatichi et al. 2009, Militino et al. 2020). The Pettitt's test (Pettitt 1979) is used to identify potential change points for the annual maximum rainfall series. Significance was determined according to *p*-values and trend/change point with 0.01, 0.05, and 0.1 levels being defined as significant.

This study shows that it is not necessarily time series that have a trend to perform better than nonstationary models, and recognition of nonstationary models solely with trend detection may be misleading. Yet obtaining nonstationary assumption from trend detection is still an up to date application. For instance, Tan and Gan (2015) make the assumption of nonstationarity based on the presence of varying trend and change points in their research. While Serinaldi et al. (2018) noticed that trend test may lack of being a tool to detect the nonstationarity and they point out that lack of rejection the H_0 cannot be solely interpret to conclude that there exists nothing for the series of interest which support the findings of this study. Totaro et al. (2019) also conclude that the results of parametric and nonparametric tests may be affected significantly by the dependence of power on the parent distribution and stationary acceptance that is made by detected weak trends which are insignificant may be misleading. This might be one of the reasons that the number of time series outperformed nonstationary models is greater than the number of time series with significant trends. Besides, it is important to mention that significance is accepted for three levels in this study (0.01; 0.05; 0.1).

Furthermore, to deal with the trend–nonstationary relationship, a better framework is needed, because significant trends and outperforming time-dependent models urge more detailed analyses of annual maximum rainfall behavior, given that these data are used for many engineering projects. Fatichi et al. (2009) explained the effect of stochastic behavior of the time series over trend and urged that this may lead to detection of significant trends even for stationary time series. Wang et al. (2020) stated the argument of American Statistical Association (ASA) which calls attention to the weakness of significance testing, which is widely used for the climate analyses. This is especially important and critical for the climate change analyses because presence of trend for the observation period is the anchor to identify the change. It should be noted that covariates other than time, such as climate indices or teleconnections, can improve nonstationary model performance and can be the subject of interest for further studies. Yilmaz (2015) point out the possibility of more intense rainfall for Antalya. He also stated the need to understand the mechanisms behind this intensification and propose to study the climate oscillations and extreme rainfall relation for further studies. The variations of trend for nearby stations and within the region suggest the need to identify the drivers of trend and the changing behavior of series. The differing trends of nearby stations and within the region also imply that more location-specific analyses are needed to explore extreme rainfall features.

However, there are some limitations of the study. The needs for further research to be discussed lastly. For the further studies, the nonstationary frequency analyses of the selected stations can be investigated. By doing this, the spatial and temporal distribution of extreme rainfall properties in terms of nonstationarities can be mapped and the effect of nonstationarity can be quantified. Moreover, while there are other covariates such as NAO, AO, etc., time was chosen since the amount of calculations and results increase for each time series, its widespread application for nonstationary models and data availability. Several other variables such as temperature, moisture, teleconnections, etc., can be incorporated into nonstationary models as covariates to capture the changes in extreme precipitation characteristics. Lastly, this study investigated city central stations, however, trends and extreme rainfall can exhibit different behavior at stations located at rural sites since Central Anatolia has comparatively a large area and show different topographical features which can affect the distribution of the rainfall.

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Compliance with ethical standards

Conflict of interest The author declares no conflict of interest.

Appendix

Model	5 min		10 min		15 min		30 min		1 h		3 h		6 h		24 h	
	AIC	BIC	AIC	BIC	AIC	BIC	AIC	BIC	AIC	BIC	AIC	BIC	AIC	BIC	AIC	BIC
Aksaray																
NST1			250.23	259.88	272.38	282.04	303.64	313.30	319.11	328.77	346.32	355.97	353.02	362.68		
NST2	201.61	211.27	249.55	259.21	272.74	282.40	302.45	312.11	316.45	326.11	344.16	353.82	352.13	361.79	369.35	379.01
NST3	199.96	207.69	247.67	255.40	270.71	278.43	300.62	308.35	316.82	324.55	346.56	354.28	356.67	364.39	368.35	376.07
NST4			248.40	256.12	271.94	279.67	301.77	309.50	317.28	325.01	345.72	353.45			367.34	375.07
NST5	199.56	207.29	248.41	256.14	272.00	279.73	301.85	309.58	317.29	325.01	345.85	353.58	352.19	359.92	367.41	375.13
ST	198.08	203.88	246.52	252.32	270.43	276.22	300.48	306.28	315.32	321.11	344.75	350.55	354.69	360.48	366.35	372.14
Ankara																
NST1	320.53	331.48			397.11	408.06	429.25	440.20	452.82	463.77	471.64	482.59	484.15	495.10	510.95	521.90
NST2			368.04	378.99	394.97	405.92	426.53	437.48	449.84	460.79	471.42	482.36	484.14	495.09	510.46	521.41
NST3	321.35	330.11	369.30	378.06	394.74	403.50	426.61	435.37	452.34	461.10	469.85	478.60	482.28	491.04	510.83	519.59
NST4	327.75	336.51			395.88	404.64	427.42	436.18	450.89	459.64	469.65	478.40	482.15	490.91	508.97	517.73
NST5	327.79	336.55	370.71	379.47	395.87	404.63	427.43	436.19	450.98	459.74	469.66	478.42	482.26	491.01	508.95	517.71
ST	326.52	333.09	369.21	375.78	394.06	400.63	425.57	432.13	450.55	457.12	467.86	474.43	480.28	486.85	511.34	517.91
Çankırı																
NST1	284.02	294.24	320.44	330.65	345.02	355.23			383.20	393.41			391.97	402.19	419.32	429.54
NST2	283.80	294.02	319.97	330.19	344.99	355.21	375.50	385.72	382.52	392.74	390.07	400.28	391.28	401.49	418.56	428.78
NST3	281.93	290.11	317.98	326.16	343.03	351.20	374.53	382.71	383.12	391.30	388.14	396.32	390.84	399.01	417.37	425.55
NST4	284.42	292.59	318.83	327.00	343.02	351.19			382.06	390.23			395.56	403.73	418.39	426.56
NST5	284.42	292.59	318.83	327.00	343.02	351.19	374.34	382.51	381.99	390.16	390.86	399.03	395.57	403.74	419.71	427.88
ST	282.42	288.55	316.83	322.96	341.04	347.17	372.59	378.72	381.00	387.13	389.55	395.68	396.58	402.71	418.59	424.72
Eskişehir																
NST1	291.54	301.67	332.26	342.39	359.77	369.90	400.44	410.57	411.48	421.60						
NST2	290.38	300.51	331.08	341.20	358.73	368.86	400.23	410.35	411.37	421.50	400.09	410.21	401.75	411.87	402.76	412.89
NST3	288.49	296.59	330.50	338.61	358.35	366.45	399.95	408.05	410.02	418.13	398.29	406.39	400.99	409.09	405.15	413.25
NST4	290.58	298.68	330.37	338.48	357.85	365.95	398.45	406.55	409.48	417.58						
NST5	290.58	298.68	330.29	338.39	357.79	365.90	398.34	406.44	409.56	417.66	398.61	406.71	401.30	409.40	402.53	410.63
ST	288.66	294.74	330.00	336.08	357.88	363.96	398.00	404.08	408.02	414.10	396.65	402.73	399.44	405.51	403.16	409.24
Karaman																
NST1	252.61	262.27	289.45	299.11	304.71	314.37	325.16	334.82	330.95	340.61			361.70	371.36	383.18	392.84
NST2	252.49	262.15	289.39	299.05	304.56	314.22	324.30	333.95	330.30	339.96	350.73	360.39	361.61	371.27	382.23	391.89
NST3	250.98	258.70	287.40	295.13	302.73	310.45	323.48	331.21	330.58	338.30	348.86	356.59	359.65	367.38	380.73	388.46
NST4	250.93	258.65	287.53	295.26	303.38	311.11	324.67	332.40	331.06	338.79			359.72	367.45	381.20	388.93

Model	5 min		10 min		15 min		30 min		1 h		3 h		6 h		24 h	
	AIC	BIC	AIC	BIC	AIC	BIC	AIC	BIC	AIC	BIC	AIC	BIC	AIC	BIC	AIC	BIC
NST5	250.91	258.63	287.52	295.24	303.38	311.11	324.70	332.43	331.04	338.77	348.89	356.62	359.72	367.45	381.24	388.96
ST	249.05	254.84	285.67	291.47	301.42	307.22	322.72	328.52	329.18	334.98	346.89	352.69	357.72	363.52	379.32	385.11
Kayseri																
NST1	281.40	291.95	338.33	348.88			391.36	401.91	414.14	424.69	423.74	434.30	429.66	440.22		
NST2	281.36	291.92	336.95	347.51	354.01	364.57	389.34	399.89	412.89	423.44	421.37	431.93	427.90	438.46	436.71	447.26
NST3	280.40	288.84	335.02	343.47	352.04	360.49	388.17	396.62	411.89	420.34	419.69	428.14	426.40	434.85	432.27	440.71
NST4	283.43	291.87	339.44	347.89	354.90	363.35	391.40	399.84	413.85	422.29	422.69	431.14	428.01	436.45	434.55	442.99
NST5	283.43	291.88	339.51	347.95	354.95	363.40	391.71	400.16	413.95	422.40	422.95	431.39	428.08	436.52	434.60	443.04
ST	281.49	287.82	338.26	344.59	353.29	359.62	391.10	397.43	412.74	419.07	423.07	429.40	426.08	432.41	432.71	439.04
Kırıkkale																
NST1	252.57	262.03	301.81	311.27	324.05	333.51	345.89	355.35	352.45	361.91	353.38	362.84	357.88	367.34		
NST2	281.36	291.92	301.80	311.26	324.00	333.46	345.63	355.08	352.37	361.83	353.29	362.75	357.92	367.38	367.61	377.07
NST3	250.61	258.18	299.85	307.42	322.46	330.02	344.44	352.01	350.86	358.43	351.32	358.89	356.10	363.67	365.63	373.20
NST4	250.91	258.48	299.99	307.56	322.04	329.61	344.04	351.60	350.46	358.03	351.43	359.00	355.87	363.44	364.85	372.42
NST5	250.92	258.48	299.99	307.56	322.10	329.67	344.43	351.99	350.90	358.46	351.45	359.02	355.90	363.46	365.62	373.18
ST	248.92	254.59	297.99	303.67	320.49	326.16	342.44	348.11	348.92	354.59	349.65	355.33	354.11	359.78	363.63	369.31
Kırşehir																
NST1	350.10	361.62	403.12	414.64	442.87	454.39	480.05	491.57	498.89	510.41	503.44	514.96	515.79	527.31	527.23	538.75
NST2	349.73	361.25	403.04	414.56	440.16	451.68	475.22	486.74	494.47	505.99	502.64	514.16	509.90	521.42	522.67	534.19
NST3	348.05	357.27	401.30	410.51	438.19	447.40	473.39	482.60	493.64	502.86	502.34	511.56	510.28	519.50	522.43	531.64
NST4	348.44	357.65	402.32	411.53	441.37	450.59	481.08	490.29	502.23	511.45	510.41	519.62	520.24	529.46	530.98	540.19
NST5	348.34	357.55	402.20	411.41	441.34	450.56	481.06	490.28	502.24	511.46	510.49	519.71	520.42	529.64	531.01	540.22
ST	347.74	354.65	401.41	408.33	439.71	446.62	479.34	486.26	500.29	507.21	509.98	516.89	520.93	527.84	529.02	535.93
Konya																
NST1	310.42	321.37	350.40	361.34			396.52	407.47	413.42	424.37	427.01	437.96	445.75	456.69		
NST2	310.48	321.43	350.38	361.33	373.10	384.05	396.18	407.13	413.34	424.29	425.80	436.75	444.20	455.15	489.98	500.92
NST3	308.99	317.75	348.50	357.26	370.93	379.68	394.29	403.05	411.90	420.66	424.08	432.84	442.13	450.89	493.21	501.97
NST4	308.85	317.61	348.40	357.16	370.79	379.55	394.66	403.42	411.98	420.74	425.08	433.84	444.51	453.26	494.70	503.46
NST5	308.86	317.62	348.40	357.16	370.80	379.56	394.66	403.42	411.97	420.73	425.10	433.86	444.91	453.67	495.32	504.07
ST	307.21	313.78	346.50	353.07	369.10	375.67	392.67	399.24	410.18	416.75	423.25	429.81	443.45	450.02	493.37	499.94
Nevşehir																
NST1	216.83	226.49	255.70	265.36	277.57	287.23	301.62	311.28	323.23	332.88	333.03	342.69	344.54	354.20	358.88	368.54
NST2	216.31	225.97	255.66	265.32	277.56	287.21	301.41	311.07	323.02	332.68	332.82	342.48	344.40	354.06	358.83	368.49
NST3	214.43	222.16	253.69	261.42	275.66	283.38	299.55	307.28	323.12	330.85	333.29	341.02	342.56	350.28	358.30	366.03
NST4	215.15	222.88	253.76	261.49	275.59	283.32	299.78	307.50	321.96	329.68	331.05	338.78	342.60	350.33	356.88	364.60

Model	5 min		10 min		15 min		30 min		1 h		3 h		6 h		24 h	
	AIC	BIC	AIC	BIC	AIC	BIC	AIC	BIC	AIC	BIC	AIC	BIC	AIC	BIC	AIC	BIC
NST5	215.16	222.88	253.76	261.49	275.58	283.31	299.78	307.51	322.28	330.00	330.96	338.69	342.64	350.37	357.06	364.79
ST	213.32	219.11	251.78	257.57	273.67	279.46	297.83	303.63	321.27	327.07	331.37	337.16	340.64	346.44	356.37	362.16
Niğde																
NST1	235.54	245.76	267.64	277.85	285.65	295.87	318.36	328.57	332.37	342.58			378.64	388.86		
NST2	235.10	245.31	266.65	276.86	283.02	293.24	317.30	327.51	329.55	339.77	360.93	371.14	375.95	386.17	406.80	417.02
NST3	233.10	241.27	264.65	272.82	281.20	289.38	315.95	324.12	328.85	337.02	360.04	368.21	374.39	382.56	404.96	413.13
NST4	234.47	242.64	267.91	276.08	288.01	296.18	328.86	337.03	343.28	351.45	366.84	375.02	380.32	388.50		
NST5			267.84	276.01	287.96	296.13	328.90	337.07	343.57	351.74	366.86	375.03	380.52	388.69	408.26	416.43
ST	232.93	239.06	266.80	272.93	286.89	293.02	327.49	333.62	342.56	348.69	365.02	371.15	380.64	386.77	406.28	412.41
Sivas																
NST1	267.92	278.23	293.00	303.30	316.96	327.26	343.33	353.63			368.50	378.80	372.38	382.68	404.11	414.42
NST2	267.91	278.21	293.21	303.52	316.58	326.89	343.24	353.54	355.45	365.75	368.36	378.66	372.34	382.64	402.64	412.95
NST3	266.28	274.52	294.24	302.48	318.28	326.53	345.13	353.37	355.92	364.16	367.89	376.14	370.65	378.89	407.10	415.34
NST4	266.38	274.63	291.73	299.97	314.99	323.23	343.10	351.35			366.55	374.80	370.38	378.62	402.20	410.44
NST5	266.47	274.71	292.00	300.25	315.20	323.44	343.23	351.47	353.98	362.22	366.65	374.89	370.41	378.65	400.50	408.74
ST	265.05	271.23	293.03	299.21	316.45	322.63	345.93	352.11	355.04	361.22	366.06	372.24	368.66	374.84	407.17	413.35
Yozgat																
NST1	269.93	280.05	305.29	315.42	333.99	344.12	360.89	371.02	373.02	383.14	394.05	404.17			417.14	427.27
NST2	269.86	279.99	305.21	315.34	333.89	344.02	360.29	370.42	371.74	381.87	391.79	401.92	394.08	404.20	414.81	424.94

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