Uluslararası Mühendislik
Araştırma ve Geliştirme Dergisi
International Journal of
Engineering Research and
Development

UMAGD, (2022) 14(1), 246-255.

10.29137/umagd.868317

Cilt/Volume:14 Sayı/Issue:1 Ocak/January 2022

Araştırma Makalesi / Research Article

Persistence of Precipitation Time Series: Kırşehir Case Study

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***Başvuru/Received**: 26/01/2021* ***Kabul / Accepted**: 16/07/2021* ***Çevrimiçi Basım / Published Online:** 31/01/2022*

***Son Versiyon/Final Version**: 31/01/2022*

Abstract

This study examines the persistence and long-term correlation of monthly and seasonal precipitation time series of the Kırşehir province (Turkey) for the period of 1960-2019, with the widely used Hurst exponent (H) and Detrended Fluctuation Analysis (DFA) methods. Both methods can be used to detect the long-term memory and correlation to be assessed as a reference of predictability. In order to support the study results, Augmented Dickey Fuller (ADF) and Mann-Kendall (MK) tests were applied to the time series under consideration. In some of the precipitation series, the evidence of persistence and long-term correlation was identified. According to the H exponent values, 10 out of 12 months, winter, and autumn seasons (with both simple R/S and corrected R/S methods), and spring and summer seasons (respectively with simple R/S and corrected R/S methods) exhibit long term correlations. On the other hand, according to the DFA scaling exponent values, 4 out of 12 months, winter and autumn seasons reveal long term correlations. When the H exponent and DFA scaling exponent values are compared only four monthly and two seasonal precipitation series are found to be consistent with each other.

Key Words

"Hurst exponent, Persistence, Detrended Fluctuation Analysis, Precipitation"

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1. Introduction

It is a common acceptance that climate change will have significant effects on the water cycle (Osborn et al., 2015). Long- and short-term climatic variability is observed all around the world and may have significant impacts on water resources (Meshram et al. 2020). In some regions, such changes are expected to change precipitation regimes (e.g., increase in the frequency and intensity of precipitation extremes as presented by Zhou et al., 2012; Papagiannaki et al., 2015). In this manner precipitation becomes the main driver for water resources both for drought and flood conditions and not only observed but also expected conditions gain importance yet because of the mechanism and dependencies behind precipitation it is not an easy process to make substantial predictions (Chandrasekaran et al. 2019).

Discovered by Hurst (1951), the Hurst phenomenon states that the variability of climate variables is not an irregular process, but also indicates that the future states of a system may be affected by the current state of the system known as long-term memory (LTM) (Xie et al. 2019). The phenomenon was first used for the flood analyses of Nile River by Hurst with a form of exponent hereafter named Hurst exponent. Since then, Hurst exponent is used for many studies ranging from hydrology to capital markets. For instance, Tatli (2015) applied H exponent for persistence of a drought index over Turkey, Agbazo et al. (2018) analyzed the long-term memory in precipitation over Benin, Correa et al. (2017) analyzed long term memory in Southern Oscillation Index (SOI) and stationary signals associated with it for Alacantara, Brasil. Moreover, Raimundo and Okamoto Jr. (2018) used H exponent for Forex securities' classification. Meshram et al. (2020) used a coupled Mann-Kendall and Hurst Exponent analyses for temperature effects over agricultural crop production in the Chhattisgarh State, India. Besides, studies support that the strength of long term memory affects the predictability of the variable of interest and it is suggested that considering the long term memory effect may improve the prediction performance (Zhu et al. (2010), Yuan et al. (2013), Yuan et al. (2014), Xie et al. (2019)).

In recent years, Detrended Fluctuation Analysis (DFA) (Peng et al. 1994) has also been used as an important tool to detect long-range correlations especially in time series with potential nonstationarities. DFA is a scaling analysis method that calculates a quantitative parameter as a representative of the long-range autocorrelation (Yue et al. 2010). Moreover, DFA is said to be enabling the correct estimation of the Hurst exponent in the context of nonstationaries (Kantelhardt, 2015). Likewise, the Hurst exponent, DFA has also been used in many studies in various areas such as hydrology, finance/stock market or health sectors (Kurnaz, 2004; Yue et al. 2010; Golinska, 2013; Marton et al. 2014; Bu and Shang, 2014; Zeybekoglu and Keskin, 2020).

Under climate change conditions, the Central Anatolia Region in which the Kırşehir provinve is located, is expected to be one of the most affected parts in Turkey (Bozoğlu et al. 2019). Mall et al. (2006) and Palmer et al. (2008) stated the sensitivity of drier and populated regions to climate change and the potential water stress around the world. Moreover, Dudu and Çakmak (2018) pay attention to the effect of extreme climatic conditions such as droughts or floods in the western and central regions of Turkey and their negative economic and agricultural impacts which are supported by Dellal et al. 2011 under climate change conditions with a projected decrease in crop yield in the Central Anatolia. Gönençgil and Acar (2021) figure out that Eastern Anatolia and Central Anatolia Regions exposed to the highest extreme humid days for summer. Bacanlı et al. (2011) investigated Palmer Drought Severity Index (PDSI), Erinc and De Martonne with monthly mean observed precipitation and temperature data and revealed that the Central Anatolian Region in Turkey has a potential to face severe drought conditions. Turkes et al. (2020) indicated that the Central Anatolian Region is one of the regions that will experience semi-arid and dry sub-humid conditions in the future while Altın et al. 2012 also stated temperature increase in all of the studied stations and decrease in mean rainfall intensity at the twelve stations including Kırşehir in their study. Oruc (2021) also stated that the Central Anatolia Region is expected face fluctuations in terms of precipitation and drought conditions Furthermore, Boyacı and Küçükönder (2021) indicated the potential water stress for the Kırşehir Province for the coming years. For this reason, the Kırşehir province was chosen for the Hurst exponent and DFA analyses.

This paper investigates long term memory and correlation of historical (1960-2019) monthly and seasonal precipitation in annual time scale by the Hurst exponent and DFA methods. Furthermore, to support and better interpret the long-term analyses of the data, Augmented Dickey Fuller (ADF) test for nonstationary signals and well-known Mann-Kendall (MK) test for trend were used.

2. Study Area and Data

2.1. Study Area

The Kırşehir province (Turkey) is located in the Central Anatolia Region which includes some parts of the Kızılırmak river basin (Figure 1). The elevation of the study area ranges from 860 m to 1310 m. The area has typical continental climatic characteristics and receives most of the annual precipitation (384.5 mm in average) in winter and spring seasons. Hot and dry summers are followed by cold winters in the study area. The average air temperature is about 11.5 ºC. Its surface area is approximately 6530 km2. The lands of the province constitutes, 0.8 percent of the country's land, 2.9 percent of the Central Anatolia Region. The coordinates of the province are 38°50'-39°50' North latitudes and 33°30'-34°50' East longitudes. Provincial territory is made up 900-1200 m. of high plateaus. There are mountains that reach 1700 m above the plateau surface. Many large and small rivers pass through Kırşehir province which Kızılırmak is one of them. Kırşehir is poor in terms of forest and generally looks like a steppe

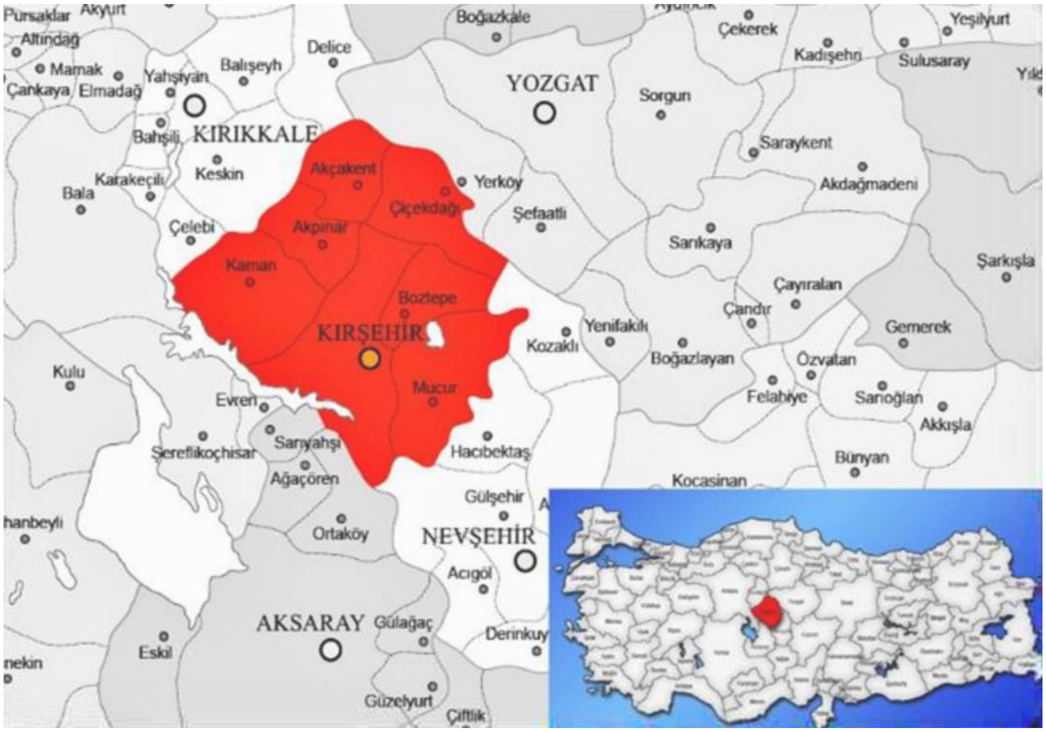

Figure 1. Location of the Study Area (Özdemir, 2020)

2.2. Precipitation Data

Daily (1960-2019) precipitation records of Kırşehir station (No:17160) were officially provided by the Turkish State Meteorological Service which were quality controlled before distributed. The monthly and seasonal precipitation amounts used in the analyses were calculated from the daily records which has continuous data from 1960 to 2019. Monthly precipitation variation during the study period is presented in Figure 2.

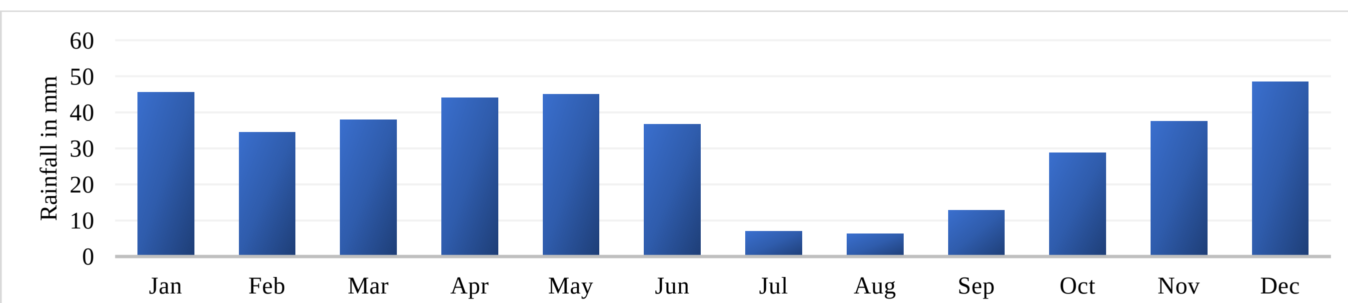

Figure 2. Monthly Average Precipitation Between 1960-2019

3. Methodology

Classification of long-term memory/persistence of the monthly and seasonal time series were investigated by Hurst Exponent DFA methods. Hurst exponents are calculated by various methods yet in this study simple and corrected R/S method is selected (Weron, 2001). R packages pracma (Borchers, 2021), nonlinearTseries (Garcia, 2021), tseries (Trapletti and Hornik, 2021) and trend (Pohlert, 2020) from the R Foundation for Statistical Computing used for the calculations.

3.1. Hurst Exponent and DFA

The Hurst exponent (H) provides a measure for the long-term memory of a time series. With values H exponent < 0.5, H exponent = 0.5, and 0.5 < H exponent < 1, it defines the dependence of future over present. Similar to H exponent, time series is classified according to the DFA scaling exponent, which $\alpha = 0.5$ indicates an uncorrelated time series, $\alpha < 0.5$ indicates an anti-correlated time series, and $0.5 < \alpha < 1$ indicates positive correlations.

Several techniques have been proposed in the literature for calculating the H exponent. In this study R/S and DFA methods were used to calculate the Hurst Exponent. More details regarding R/S can be found in (Weron, 2001; Hurst, 1951; Peters, 1994; Taqqu et al., 1995; Mandelbrot and Wallis, 1969).
Considering the R/S method; time series of length L divided into d subseries of length n and for each subseries m = 1, . . ., d: the data ($Z_{i,m}$) is normalized by subtracting the sample mean $X_{i,m}=Z_{i,m}-E_m$ for i=1, . . . ,n;

- cumulative time series $Y_{i,m} = \sum_{j=1}^{i} X_{j,m}$ for i = 1, . . . ,n; is obtained
- the range $R_m = \max\{Y_{1,m}, \ldots, Y_{n,m}\} - \min\{Y_{1,m}, \ldots, Y_{n,m}\}$; is calculated
- the range Rm/Sm is rescaled and the mean value of the rescaled range for all subseries of length n; is calculated

$$\left(\frac{R}{S}\right)_n = \frac{1}{d}\sum_{m=1}^{d}\frac{R_m}{S_m} \quad (1)$$

$$\left(\frac{R}{S}\right)_n = cn^H \quad (2)$$

$$\log\left(\frac{R}{S}\right)_n = \log(c) + H\log(n) \quad (3)$$

DFA can be found in (Peng et al., 1994, Weron, 2001; Penzel et al. 2003; Bryce and Sprague, 2012; Hardstone et al. 2012). Considering the DFA, time series of length L divided into d subseries of length n and for each subseries m = 1, . . . , d:

- a cumulative time series $Y_{i,m} = \sum_{j=1}^{i} X_{j,m}$ for i = 1, . . . , n; was created
- a least-squares line $Y_m(x) = a_m x + b_m$ to $\{Y_{1,m}, \ldots, Y_{n,m}\}$; fitted
- the root mean square fluctuation (i.e. standard deviation) of the integrated and detrended time series is calculated

$$F(m) = \sqrt{\frac{\sum_{i=1}^{n}(Y_{i,m} - a_m i + b_m)^2}{n}} \quad (4)$$

$$F(n) = \frac{1}{d}\sum_{m=1}^{d} F(m) \quad (5)$$

The value of H can be obtained by performing the same simple linear regression like in the R/S method.

3.2. Augmented Dickey Fuller (ADF) Test

ADF test is used to detect the stationarity in time series of a given period. Augmented Dickey Fuller (ADF) (Dickey and Fuller, 1979; Said and Dickey, 1984; Fuller, 1996) which is still a unit root test for stationarity, was revised to tackle autocorrelation problems from DF test (Dickey and Fuller, 1979). This ADF test is conducted by augmenting the DF equation in which the lagged difference form of the dependent variable ΔX_t is added. The new equation takes the following form;

$$X_t = \rho X_{t-1} + \sum_{j=1}^{p}\psi_j \Delta X_{t-j} + u_t \quad \text{or} \quad \Delta X_t = \pi X_{t-1} + \sum_{j=1}^{p}\psi_j \Delta X_{t-j} + u_t \quad (6)$$

$$\Delta X_{t-1} = (X_{t-1} - 2), \Delta X_{t-2} = (X_{t-2} - X_{t-3}), \text{etc.} \quad (7)$$

3.3. Mann-Kendall Trend Test

There are two categories of trend test in general, namely parametric and non-parametric tests and the latter are considered to be more appropriate for the trend detection of hydro-meteorological variables.

The MK trend test (Mann, 1945; Kendall, 1975) which is also a non-parametric and rank based test, was used to detect trends in the precipitation data in this study.

The MK test was formulated by the following equations:

$$S = \sum_{i=1}^{n-1}\sum_{j=i+1}^{n} \mathrm{sgn}(x_j - x_i) \quad (8)$$

here S is the test statistic.

$$\mathrm{sgn}(x_j - x_i) = \begin{cases} +1 \\ 0 \\ -1 \end{cases}\begin{cases} (x_j - x_i) > 0 \\ (x_j - x_i) = 0 \\ (x_j - x_i) < 0 \end{cases} \quad (9)$$

$$V(S) = \frac{n(n-1)(2n+5) - \sum_{i=1}^{m} t_i(t_i-1)(2t_i+5)}{18} \quad (10)$$

$$Z = \begin{cases} \frac{S-1}{\sqrt{V(S)}} & , S > 0 \\ 0 & , S = 0 \\ \frac{S+1}{\sqrt{V(S)}} & , S < 0 \end{cases} \tag{11}$$

When the absolute value of Z is greater than the critical value Z_α, the null hypothesis, H0, that there is no trend is rejected. Significance level α can be defined by the user and can get different values regarding the desired significance of the study (Mann 1945; Kendall 1975; Militino et al. 2020).

4. Results and Discussion

The Hurst exponent and DFA scaling exponent values of the precipitation time series for each season and calendar month were evaluated at an annual time scale together with annual totals for the period of 1960-2019. Simple and corrected H exponents were calculated for the precipitation series. Furthermore, three DFA scaling exponents were calculated based on window size and window size range to prevent sensitivities regarding window size. The means of calculated three DFA scaling exponents for each month and season were then used for the comparison with the H exponent values of same precipitation series. At first summary statistics of monthly, seasonal, and annual precipitation series are given in Tables 1. and 2, respectively to make a brief description of the precipitation characteristics for the study area. In general, the mean and standard deviation (SD) values of July, August and September are smaller than the rest of the months. However, the precipitation amounts in these moths show relatively higher variability (high coefficient of variation, CV) compared to those in other months. In addition, the statistical values indicated that January, June, July, August, September, and October accommodate positively, and highly positively skewed precipitation which indicates the distortion of the series from normal distribution. When kurtosis values are considered for outliers, it is convenient to conclude that January, June, July, August, September, and October months showed remarkable sign of outlier precipitation values for the Kırşehir station which can be one of the reasons of high cv values of July, August, and September monthly precipitation amounts.

Table 1. Summary Statistics of Monthly Precipitation

	Jan	Feb	Mar	Apr	May	Jun	Jul	Aug	Sep	Oct	Nov	Dec
Mean	45.56	34.53	37.94	44.04	45.02	36.76	7.00	6.26	12.78	28.80	37.56	48.54
SD	29.22	19.32	21.15	22.54	26.73	30.10	9.34	11.24	14.45	24.76	26.72	26.64
CV	0.64	0.56	0.56	0.51	0.59	0.82	1.33	1.80	1.13	0.86	0.71	0.55
Skewness	1.02	0.96	0.94	0.53	0.89	1.46	1.73	2.63	1.55	1.37	0.85	0.18
Kurtosis	1.16	0.85	0.47	-0.28	0.27	3.14	2.43	7.75	2.52	2.91	0.35	-0.97

Considering the seasonal precipitation, the mean- and standard-deviation values of Summer and Autumn exhibited smaller values. Summer season showed positive skewness while the rest of the seasons show low skewness values. Moreover, only the summer season had a positive kurtosis which is also the highest among the other seasons that have lighter tails.

Table 2. Summary Statistics of Annual and Seasonal Precipitation

	Annual	Winter	Spring	Summer	Autumn
Mean	384.80	128.60	127.00	50.03	79.15
SD	73.19	49.71	40.64	38.49	37.95
CV	0.19	0.39	0.32	0.77	0.48
Skewness	0.16	0.40	0.21	1.39	0.56
Kurtosis	-0.92	-0.88	-0.50	2.25	-0.15

In Table 3., ADF test, MK test, H exponent and DFA scaling exponent results were exhibited for the monthly precipitation series. Depending on the H and DFA results, monthly precipitation series showed various persistence and long-term correlation characteristics.

Table 3. ADF Test-MK Test-H Exponent-DFA Results of Monthly Precipitation

	ADF p value	MK z value	MK p value	Simple R/S H	Corrected R/S H	DFA1	DFA2	DFA3	Avg
January	0.082	0.497	0.619	0.579	0.722	0.58	0.60	0.61	0.60
February	0.010	-1.403	0.161	0.571	0.796	0.66	0.65	0.66	0.66
March	0.051	-0.651	0.515	0.535	0.460	0.38	0.33	0.43	0.38
April	0.241	-1.410	0.159	0.611	0.862	0.47	0.41	0.52	0.47
May	0.010	-0.472	0.637	0.470	0.532	0.23	0.22	0.22	0.22
June	0.011	-0.159	0.873	0.520	0.616	0.36	0.35	0.37	0.36
July	0.010	1.676	0.094	0.415	0.307	0.28	0.27	0.30	0.28
August	0.414	1.569	0.117	0.555	0.692	0.60	0.60	0.50	0.57
September	0.010	0.185	0.853	0.545	0.679	0.43	0.47	0.46	0.45
October	0.054	1.040	0.299	0.536	0.663	0.48	0.46	0.44	0.46
November	0.333	0.593	0.553	0.611	0.664	0.71	0.68	0.71	0.70
December	0.014	-1.142	0.254	0.531	0.692	0.31	0.31	0.36	0.33

The H values ranges between 0,415 to 0,611 for simple R/S method and 0,307 to 0,862 for the corrected R/S method. Table 3 suggests that the precipitation record in Kırşehir is most likely to contain the Hurst effect of dependence and persistence because of its relative instability. The Hurst exponent (H) provides a measure for the long-term memory of a time series. With values H exponent < 0.5, H exponent = 0.5, and 0.5 < H exponent < 1, it defines the dependence of future over present. Similar to H exponent, time series is classified according to the DFA scaling exponent, which $\alpha = 0.5$ indicates an uncorrelated time series, $\alpha < 0.5$ indicates an anti-correlated time series, and $0.5 < \alpha < 1$ indicates positive correlations.

The results show convincing evidence of the Hurst effect in the precipitation series except March, May, and July months which have H values of 0.535, 0.470, 0.415, and corrected H values of 0.460, 0.532, 0.307. It can be concluded from the H values that monthly time series show evidence of long-term persistence for the period 1960- 2019.

Considering the DFA, results of the three scaling exponents of annual time series of monthly precipitation showed closer values. Averages of these values ranges from 0.22 to 0.70 whereas only four of the precipitation series, namely, January, February, August and November show signal of persistence.

The precipitation series that were identified as persistent also show long-term dependence based on the Hurst exponent values. Furthermore, among these months, January, August and November precipitation series also showed nonstationary characteristics and it can be concluded that DFA analyses successfully overcome the nonstationarity, which is also indicated by ADF results, based on the calculated scaling exponent for these series.

Based on the combined results of Hurst exponent and DFA methods, January, August, and November monthly precipitation values of Kırşehir station are expected to increase while February precipitation will tend to decrease. These results were interpreted based on the dependence of future over past phenomena by using the DFA and H results and the current tendencies of the monthly time series that were revealed by MK test results. In addition, when only Hurst exponent results were considered, April, June and December precipitation amounts are also expected to decrease, and October precipitation is expected to increase while September is expected to show no significant increase or decrease.

Furthermore, nonstationarity and trend characteristics show different properties according to ADF and MK test for each time series. MK test results show both increasing and decreasing trends yet none of these trends are significant at five percent significance level. Moreover, nonstationary characteristics also show variations among the months and half of the precipitation series show nonstationary signals according to ADF test results. Performing the ADF test showed that two of the three time series that exhibit no clear evidence of long-term dependence also show significant stationary characteristics. On the other hand, it is not possible to make a concrete conclusion regarding relation between nonstationary properties, trend tendencies and Hurst exponent of the precipitation series.

Table 4. ADF Test-MK Test-H Exponent-DFA Results of Annual and Seasonal Precipitation

	ADF p value	**MK z value**	**MK p value**	**Simple R/S H**	**Corrected R/S H**	**DFA1**	**DFA2**	**DFA3**	**DFA Avg.**
Annual	0.010	0.089	0.929	0.482	0.346	0.18	0.18	0.24	0.20
Winter	0.032	-1.384	0.166	0.610	0.809	0.58	0.59	0.63	0.60
Spring	0.129	-0.702	0.483	0.504	0.483	0.44	0.40	0.45	0.43
Summer	0.022	0.351	0.726	0.492	0.574	0.31	0.28	0.33	0.31
Autumn	0.310	1.435	0.151	0.609	0.818	0.76	0.73	0.67	0.72

In addition to monthly precipitation, annual and seasonal precipitation were also investigated. Nonstationary and trend characteristics also show different properties according to ADF and MK test for each time series as they were in monthly analyses. MK test results show increasing trend for annual, Summer and Winter precipitation amounts and decreasing trend for winter and spring precipitation amounts but none of these trends are significant. Spring and autumn precipitation also show nonstationary behavior according to ADF test results. The H values ranges between 0.482 to 0.610 for simple R/S method and 0.346 to 0.818 for the corrected R/S method while DFA scaling exponent average values range from 0.20 to 0.72. Considering the DFA results with Hurst exponent for annual and seasonal precipitation series, winter and Autumn seasons indicate persistence. While there is no significant relation between nonsationarity and trend of the time series, Hurst coefficient and DFA scaling exponent show increasing persistence with increasing trend magnitude that is independent from the direction of the trend such as Autumn MK test z-value of 1.435 and DFA scaling exponent value of 0.72, Winter MK test z-value of -1.384 and DFA scaling exponent value of 0.60 or Spring MK test z-value of -0.702 and DFA scaling exponent value of 0.43. On the other hand, this is not valid for monthly precipitation series.

Both H and DFA methods show similar results for annual and seasonal series however, the results were different for the monthly precipitation series. Nevertheless, there are precipitation series such as January, February, August and November that H exponent and DFA results agree on a nonrandom process as Koutsoyiannis, (2020) indicated the enhanced pattern with the H approaching 1. Between 0.5-1.0, precipitation series of the study area can said to be trend reinforcing which means increases (decreases) in the series of January, February August, November months and Winter and Autumn seasons will probably be followed by increase (decrease). Conversely, for the rest of the precipitation series up values are more likely followed by down values and vice versa because of the expected mean reverting behavior according to combined H and DFA results. Despite the lack in identifying significant trends in the series, the persistency features evidenced by the Hurst exponent and DFA scaling exponent can be extended to address the precipitation intensification for the trend positive and desertification for the trend negative periods and notices for the further studies.

Chandrasekaran et al. (2019) also found that the predictability of time series in their study is higher with corresponded overall H exponent >0.5. It can be said that higher persistence and correlation will probably affect the predictability of precipitation series in a positive way. Tatli (2015) indicated that the term “persistence” may also be considered as a criterion to be applied as a predictability measure while Onyutha (2020) and Koutsoyiannis (2020) also links the persistence and temporal change for the hydrological processes. Considering the above-mentioned studies precipitation series with H exponent and/or DFA scaling exponent > 0.5 in this study can also be considered more predictable and present status can be considered more comprehensively while making future predictions. Kantelhardt (2015) stated that it is vital to compare DFA results with other methods such as spectral or wavelet analyses that is one of the reasons in this study why results of the H exponent and DFA analyses combined for deriving conclusions.

On the other hand, data length in this study is 60 years and to draw a more precise conclusion it should be vital to use longer time series for such analyses. Kantelhardt (2015) indicated the variations of the degree persistence with different time scales. Lopez-Lambrano et al. 2018 stated the effect of climate, temperature, altitude, and the precipitation regime of the area of interest over H exponent and indicated the varied tendency of H value with different time scales. The detrended fluctuation analysis (DFA) is also said to be less affected by the extreme values than R/S analyses (Hacınlıyan and Kandıran, 2015). One reason of the difference between H and DFA results can be for this. Barbulescu et al. (2010) also mentioned the method dependency of the results of R/S method and discordance with the statistical tests. Results of this study also revealed no significant relation between the results of statistical tests for trend or nonstationarity, and the persistence/correlation behavior of the time series that can be generalized.

5. Conclusions

In this article the results of persistence and long-term correlation analysis for monthly, seasonal and annual precipitation time series of 1960-2019 were analyzed and also were compared to the results of nonstationarity and trend detecting statistic tests. Long-term persistence and correlation did not exhibit remarkable concordance. However, within various precipitation series, evidence of persistence and long-term correlation was identified. According to H exponent values of simple R/S and corrected R/S methods, 10 out of 12 months and winter, spring (only simple R/S), summer (only corrected R/S) and autumn season and according to DFA scaling exponent values 4 out of 12 months and winter and autumn seasons exhibit long term correlation. On the other hand, when the H exponent and DFA scaling exponent values compared only four monthly and two seasonal precipitation series concluded to be consistent with both H exponent and DFA scaling exponent results. This can be interpreted that to gather reliable predictions these results must be properly considered. Long-term memory and correlation are accepted the sign of predictability. Further studies are needed to investigate the possible relationship, to compare with traditional approaches and to figure out the importance of long-term memory and correlation when predicting future for the hydrological variables. There is also need of quantification the long-term memory and incorporating them to predictive models which only few studies interested best of the author's knowledge.

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