Available online at www.sciencedirect.com

ScienceDirect

Procedia Earth and Planetary Science 16 (2016) 156 – 165

Procedia
Earth and Planetary Science

The Fourth Italian Workshop on Landslides

Variability and trends in streamflow in northeast United States

Gustavo Marini[a]*, Raffaele Zollo[a], Nicola Fontana[a], Maurizio Giugni[b], Vijay P. Singh[c]

[a]Department of Engineering, University of Sannio, piazza Roma, 21, 82100 Benevento, Italy
[b] Department of Civil, Architectural and Environmental Engineering, University of Naples "Federico II", via Claudio 21, 80125 Napoli, Italy
[c]Department of BAE, Texas A and M University, 321 Scoates Hall, 2117 TAMU, College Station, Texas 77843-2117, U.S.A

Abstract

There is general consensus that climate is undergoing change but whether climate change is occurring or not is still being debated in certain scientific, political, and religious quarters. Hydrologic variability influences the design of civil works and assessment of long-term climate change would help improve design criteria.To this end,long-term variability of streamflow was estimated using Shannon entropy. Three statistical tests were applied to determine trends in annual and seasonal daily streamflow with 5% two-sided confidence limit. Daily streamflow data spanning 70 years (from 1943 to 2012) from 669 stream gauge stations located in 23 states in the northeastern part of United States of America, covering six different water regions were employed.The time variability of annual and seasonal daily streamflow was assessed using the *Mean Decadal Apportionment Disorder Index* (*MDADI*).Analysis showed that in all cases minimum and maximum streamflows had higher variability than average and median streamflows.A significant number of stations exhibited trends.Considering annual minimum, average and median daily streamflows, approximately 50% of the stations followed trends and for almost all these stations trendswere increasing. Only for annual maximum daily streamflow, 15% of the stations showed increasing trend and 10% decreasing trend. In terms of geographical distribution, the stations with increasing trend were essentially located along the Atlantic coast and near Great Lakes and in the Upper Mississippi Water Region. Similar considerations apply for seasonal time series as well.

Peer-review under responsibility of the organizing committee of IWL 2015

*Keywords:*variability; trend analysis; entropy;streamflow;disorder index.

* Corresponding author. Tel.: +39-0824-305510 ; fax: +39-0824-325246.
*E-mail address:*gustavo.marini@unisannio.it

Peer-review under responsibility of the organizing committee of IWL 2015
doi:10.1016/j.proeps.2016.10.017

1. Introduction

The occurrence of climate change is not without controversy. Since hydrologic variability influences the design of civil works, assessment of long-term climate change would nevertheless help improve design criteria.

Global warming intensifies the hydrological cycle and thus increases globally averaged precipitation, evaporation, and runoff[1]. Changes in the hydrologic cycle severelyimpact the amount, timing, and distribution of rain, evaporation,temperature, snowfall, and runoff, leading to changes inthe availability of water as well as in the competition for water resources.These changes are also likely in the timing, intensity, andduration of water related-disasters, i.e., landslides, floods, droughts,with associatedchanges in water quality[2].

Several studies reported large increasesin precipitation and streamflow across the United States over thesecond half of the 20th century, with the largest increases generallybeing reported in the fall precipitation[3,4] and low to moderate flows[5,6,7]. All water resourcesregions of the conterminous U.S. between 1940 and 1999 exhibit increased streamflows: the patterns of these increases ismost pronounced in the central two-thirds of the nation and, to a lesser extent, in the eastern coastal regions and in the Great Lakes basin[8].

Most studies have investigated the existence of trends in the historical streamflow data, without defining the temporal variability and the possible mutual influence.To that end, anentropy-based approach[9] seem to be an attractive approach forevaluating the variability/disorder based on streamflow patterns within a region. As well statistical tests can assess the existence of trend.

2. Study area and streamflow data set

The data set consisted of records of daily streamflow of water courses throughout the continental United States, obtained from the*National Water Information System* (*NWIS*) database of the *U.S. Geological Survey*,available online[10]; there are daily data of more than 25000 measuring stations of both flow andwater level of rivers and lakes. The values contained in this database can be "approved", whereby the quality is guaranteed and the data are eligible for publication, or "provisional", especially for the most recent data, whereby the accuracy is not verified and the data are subjected to possible revision.

The U.S.Water Resources Council defined 21 major geographic areas, or regions, in order to assess the state of water resources throughout the nation[11].For the selection of data, we firstidentified stations located within the northeast United States, between Souris-Red-Rainy and New England regions.Then, we assessed for different time periods record lengths from 30 to 110 years (with steps of 10 years) and the number of stations for which the corresponding time series showed a percentage of missing values less than 0.1%.Hence, weidentified 669 stations across the study areawith period of record of 70 years from 1943 to 2012.The location of 669 stream gauge stations within each of six Water Resource Regions of the northeast United States are shown in Fig. 1.

For each of the selected stations, whereby the average daily streamflow time series are available, the corresponding annual and seasonal time series relating to minimum (Q_0), median (Q_{50}), maximum (Q_{100}) and average values (Q_{mean}) were obtained. For the annual series the reference period was the calendar year (January to December), while the seasonal series spanned the period from December to November: in particular, the winter season falls within in the months from December to February.

3. Data analysis and discussion of results

3.1. Definition of time series to be analyzed

Starting from the daily streamflows time series, the corresponding annual and seasonalseriesof minimum, median, average and maximum values were extracted for each station. A total of 20 time series were obtained (annual and seasonal series for each of the four values).

For each time series, the time variability was first assessed on a decadal basis using a Shannonentropy-based approach. The identification of trends within the time series and the correlation between temporal variability and trends was further discussed.

In addition, the variability/trend analysis for annual and seasonal time series of Q_{mean} was performed in order to compare the analogous results obtained for precipitation[12],so as to highlight the possible spatial correlation.

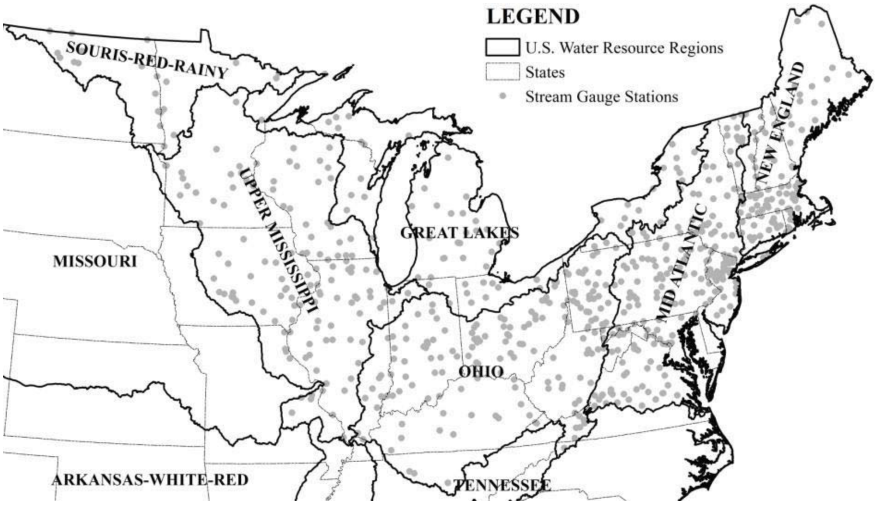

Fig. 1. Stream gauge stations used in the study and map of the U.S. Water Resource Regions.[11]

The entropy concept was used in this study to assessthe variability/disorder of streamflows time series. The analysis of spatial distribution of the results for each station allowed detecting regions of high/low variability.Entropy[13] is a measure of dispersion, uncertainty, disorder and diversification[14,15]. Singh[16] has provided a review of entropy applications in hydrology[12,17] and water resources[18,19,20,21]. The definition of Shannon entropy$H(X)$, in discrete form, can be expressed as:

$$H(X) = -\sum_{k=1}^{K} p(x_k) \cdot \log[p(x_k)] \tag{1}$$

where$H$is the entropy of a discrete random variable$X$with possible Kvalues (x_1, x_2, …, x_k, …,x_K); and $p(x_k)$ is the distribution functionof$X$.The probability $p(x_k)$ is based on the empirical frequency of values of$X$. With the base of logarithm being 2, and the unit of entropy is bit.H reaches its maximum value if all states are equiprobable orthere is more evenness in the probabilities of random values, therefore if we have no indication whatsoever to assume that one state ismore probable than another state. Thus, H expresses our uncertaintyor ignorance about the system's state. It is clear that H is equal to 0 if and only if the probability of a certain state is 1 (and of all otherstates 0). In that case, we have maximal certainty or completeinformation about the state the system is in.

Based on the Shannon entropy concept the computation of *Decadal Apportionment Entropy*(*DAE*), which measures the randomness of the time series data on a decadal basis, is possible as:

$$DAE = -\sum_{i=1}^{10} \frac{x_i}{DR} \cdot \log_2\left(\frac{x_i}{DR}\right) \tag{2}$$

where$x_i$is the value of the variable for the i-th year considered, while DR is the sum of x_i over 10 years.The ratio x_i/DR defines the occurrence probability of x_i. In this form, DAE measures the temporal variability of x_i over ten years.In this study, the variability is calculated as the difference betweenthe maximum possible entropy, which is equal to logarithm of 10 when the analysis is based on the decadal apportionment entropy, and the actual entropy obtained for the time series. In this terms it is denoted by the disorder index known as*Decadal Apportionment Disorder Index*(*DADI*):

$$DADI = \log_2(10) - DAE = \log_2(10) + \sum_{i=1}^{10} \frac{x_i}{DR} \cdot \log_2\left(\frac{x_i}{DR}\right) \tag{3}$$

Entropy, as a measure of variability, depends exclusively on the data values and not on how the data occur over time. Consequently, the time pattern does not affect the *DADI*. *DADI* reaches a maximum value (equal to $\log_2 K$) if all the values except one are null. Otherwise, *DADI* is null (minimum) when all data are the same. The more narrow the range of values, the less the series variability, so the higher the variability, the higher the disorder index.

Finally, long-term variability can be measured by computing the Mean *Decadal Apportionment Disorder Index*(*MDADI*) that is the *mean value of DADI* calculated over the entire time of observation:

$$MDADI = \frac{1}{N} \cdot \sum_{i=1}^{N} DADI_i \tag{4}$$

where$N$ is the number of *DADI* values.

In the present paper the time variability of minimum (Q_0), average (Q_{mean}), median (Q_{50}) and maximum (Q_{100}) daily streamflows, for both annual and seasonal time series, was assessed using *MDADI*[22,23]. If *MDADI* is null at a certain station, then the analyzed variable is uniform over time. In contrast, high values imply a high temporal variability.

Mean or median value of*MDADI*for all stations gives information about the average (among allstations) time variability, whereas the standard deviation provides useful information on the spatial distribution of variability of analyzed variables. If there is nospatial variability, all stations have the same value of *MDADI* and standard deviation is null. If the standard deviation is greater sothe spatial variability is higher.

3.2. Variability of annual and seasonal mean of daily streamflows

MDADI was computed forannual and seasonal values of mean of daily streamflows. The main statistical propertiesof the time series are given in Table 1. Due to the smaller values of*MDADI*, the annual time series shows less temporal variability than seasonal. Furthermore, since the annual time series shows values quite similar to *MDADI* for all the stations (thus resulting ina low standard deviation), the same exhibits a lower disorder than the corresponding seasonal series.De Martino et al.[12] found similar results for annual and seasonalprecipitation, thus confirming the strong relationshipbetween rainfall and runoff (the latter represented by average annual streamflows).

Spatial distribution of annual time series *MDADI*is given in Fig. 2.The diameter of the circles depends on the values of *MDADI*:the greater the diameter, the higher the variability.Annual time series exhibituniformly low values of *MDADI*within all the analyzedWater Resource Regions, thus resulting in a low spatial variability.Only a few stations located in the Souris-Red-Rainy region and in the western part of the Upper Mississippishow greater variability.

Table 1. Statistical properties of MDADI for time series of annual and seasonal mean of daily streamflows.

Property	Annual	Winter	Spring	Summer	Fall
Mean	0.084	0.175	0.117	0.270	0.346
Median	0.055	0.120	0.080	0.239	0.285
Std Dev	0.103	0.165	0.123	0.164	0.243

The seasonal time series showed higher average temporal variability in fall, as indicated by the average (or median) value in Table 1. The lower variability occurredduring spring, while in winter and summer intermediate values are calculated.De Martino et al.[12]found the analogous results for precipitation variability, thus could reflect the effect of the variability of seasonal precipitation on corresponding runoff.

The spatial distribution of seasonal variability (Figs. 3a-3d) showedthat stations with high values of *MDADI*are in greater numbers than those exhibiting annual variability.The Souris-Red-Rainy region and the western part of the Upper Mississippi always showed the highest variability, whatever the season. In addition, when passing from spring to fall, a large increase in areas of high variability can be identified, especially for Ohio, Mid-Atlantic and southern New England. The Great Lakes region and the northern part of New England alwayshad low variability, whatever the season.

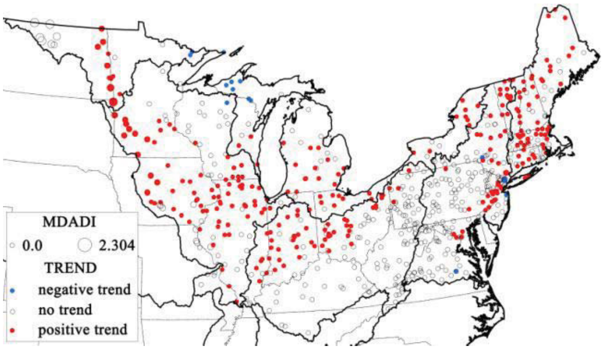

Fig. 2. Variability and trend in annual mean of daily streamflow.

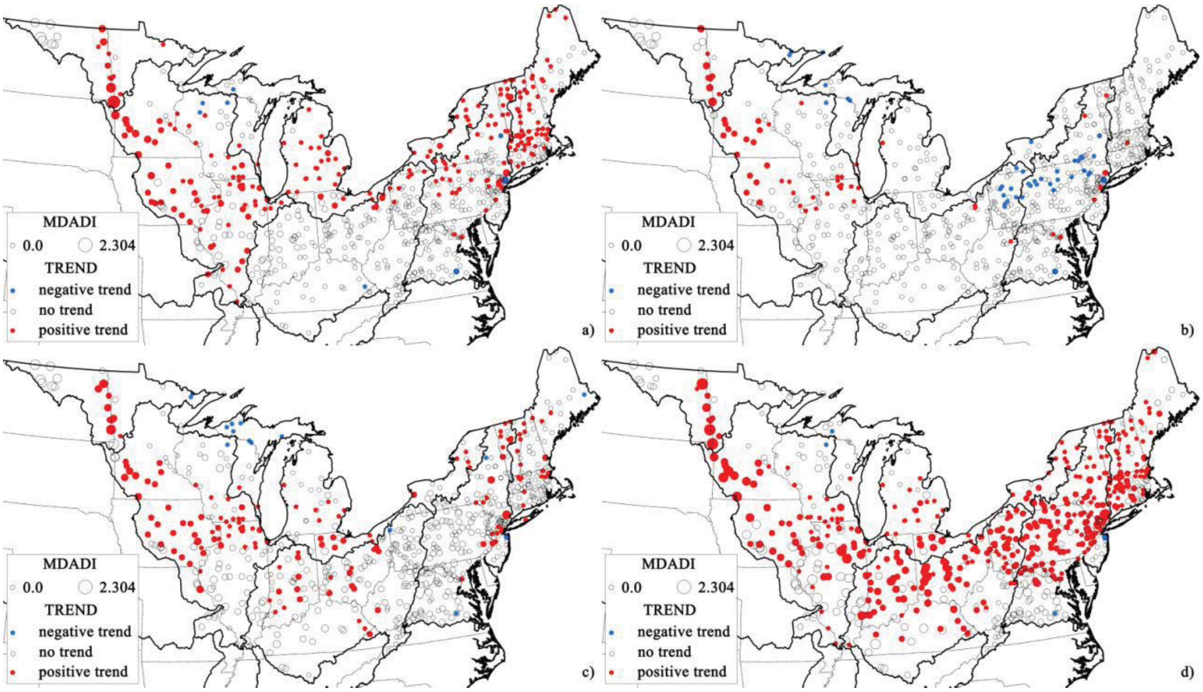

Fig. 3. Variability and trend inmean of daily streamflows in winter (a), spring (b), summer (c),fall (d).

3.3. Variability of annual and seasonal percentiles of daily streamflows

The variability through *MDADI*was investigated for several percentiles of daily streamflows, for both annual and seasonal time series: minimum (Q_0), median (Q_{50}) and maximum(Q_{100}) streamflow.The main statistical propertiesof the time series are listed in Table 2.The mean values of *MDADI* for Q_0 showed temporal variability in the annual series intermediate with respect to seasonal variability, with a standard deviation close to the maximum values observed for the summer and fall seasonal series.

The Q_{50} and Q_{100} time series showed trends similar to Q_{mean}, for both annual and seasonal values, with annual variability lower than seasonal one. Results for seasonal series of both percentiles showed higher variability in fall.The lowestvariability was identifiedduring spring, whereas for winter and summerintermediate values were calculated.

The spatial distributions of the variability for the annual series of minimum, median and maximum values of daily streamflows are shown, respectively, in Figs. 4-6.

Table 2. Statistical properties of *MDADI* for time series of annual and seasonal percentiles of daily streamflows.

	Q_0					Q_{50}					Q_{100}				
Property	Annual	Winter	Spring	Summer	Fall	Annual	Winter	Spring	Summer	Fall	Annual	Winter	Spring	Summer	Fall
Mean	0.229	0.222	0.171	0.238	0.282	0.131	0.201	0.135	0.231	0.334	0.161	0.277	0.188	0.487	0.521
Median	0.128	0.152	0.103	0.145	0.181	0.088	0.141	0.086	0.184	0.264	0.136	0.223	0.156	0.468	0.480
Std Dev	0.289	0.228	0.221	0.269	0.288	0.142	0.191	0.155	0.189	0.258	0.114	0.207	0.129	0.217	0.273

The Souris-Red-Rainy region and the western part of the Upper Mississippi River basin always showedthe highest variability, whatever the percentile. When passing from Q_0 to $Q_{50}$to Q_{mean}, the extension of areas with high variability decreased, whereas a slightincrease was observed forQ_{100}.The lower part of the Atlantic coast had high variability in Q_0 and Q_{100}, while the northern central regionof Ohio had high variability in Q_0 and Q_{50}. The Great Lakes region and the northern part of both New England and Mid-Atlantic had always low variability, whatever the percentile.For all the percentile time series, seasonal patterns in space and time were similar to the corresponding annual patterns.

According to Tootle et al.[24], the variability of streamflowscan be explainedby the Pacific and Atlantic Ocean Sea Surface Temperature (SST) variability.The authorshave identified the response of Continental U.S. streamflow to oceanic/atmospheric phenomena such as the El NiñoSouthern Oscillation (ENSO), the Pacific Decadal Oscillation (PDO), and the Atlantic Multidecadal Oscillation (AMO).Such phenomena have different periodicity: while interannual ENSO experiences a 2-7 year periodicity, the interdecadal PDO and AMO exhibit long-term (e.g. 25-30 year) periodicity of warm and cold phases.Results of the present study wereconsistent with those proposed by Tootleet al.[24], since the stations with higher variability are located within the regions influenced by one or more phases of PDO and/or AMO.The Souris-Red-Rainy regionis influenced by the warm phase of AMO; Upper Mississippi region is influenced by both cold and warm phases of AMO and by warm phase of PDO. The lower part of the Atlantic coastis affected by both warm phase of PDO and cold phase of AMO,while the northern central regionof Ohio is only influenced by cold phase of PDO. Finally, the Great Lakes region and the northern part of both New England and Mid-Atlanticdo not fit within the regions highlighted in the study of Tootle et al.[24].

3.4. Trends of time series

In order to assess the existence of trends in the time series of minimum (Q_0), average (Q_{mean}), median (Q_{50}) and maximum (Q_{100}) daily streamflows, for both annual and seasonaltime series, the *Mann-Kendall test*[25,26], *Spearman's Rho test*[27] and *Sen's slope test*[28] were employed. For the sake of brevity, the trend test equations are not given here. A brief description of the tests can be found in De Martino et al.[12]. In this study, the 5% two-sided confidence limit was used forthe tests and it was assumed that only the data series for whichall tests rejected the null hypothesis followed a statistically significant trend.

3.5. Trend in annual and seasonal mean of daily streamflows

The series following trends in annual mean ofdaily flow are shown in Fig. 2. The red circles indicate stations with positive trend, blue circles negative trend. The white circles show stations in which there are no statistically significant trends, or in which the null hypothesis has not been rejected for at least one of the tests.

Test results for Q_{mean}andpercentilesQ_0, Q_{50} and Q_{100} are given in Table 3. The annual series exhibit positive trendsfor 278 stations, mainly located along the Atlantic coast, in both the central part of Great Lakes and the Upper Mississippi regions, and in the central part of Souris-Red-Rainy region. Only a few stations exhibited negative trends, all located in the northwest of the Great Lakes region. The remaining stations do not show statistically significant trend.

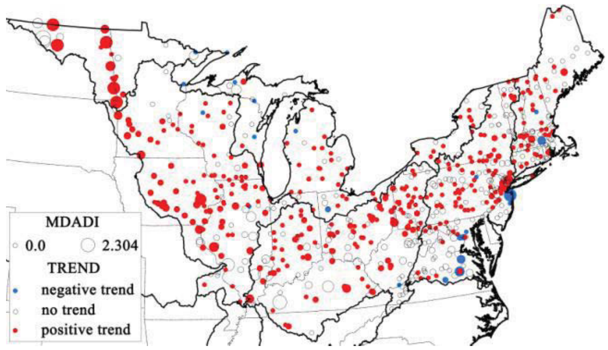

Fig. 4. Variability and trend in annual minimum (Q_0) of daily streamflows.

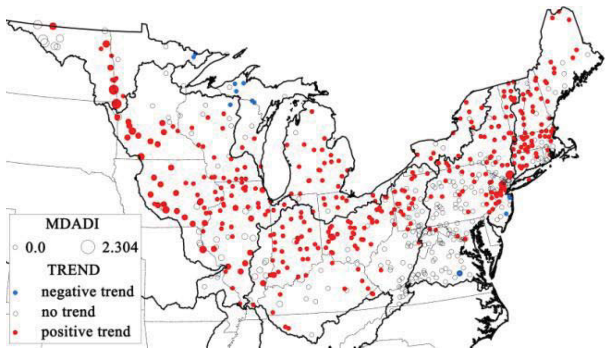

Fig. 5. Variability and trend in annual median (Q_{50}) of daily streamflows.

When comparing such results with those of variability analysis, it resulted that stations with high variability for Q_{mean} are located in the western part of the investigated area,consequently no correlation can be established between variability and trend.In addition, the annual series of precipitation with trend[12]are approximately located in the same areas. As the stations with positive trend are significantly greater than those with negative trend (as it occurs for precipitation), it results an increased Q_{mean}within the investigated regions.Trend analysis was also carried out for the seasonal time series. Results are summarized in Table 3, whereasthe spatial representation is shown in Figs 3a-3d.

Fall is the season with the highest number of series with positive trend (63.2% of 669 stations), followed by winter and summer. Only a few stations exhibit negative trend, mostly in spring. As a result, in fall and winter the greatest percentage of positive trend can be noticed, whereas in spring and summer the most negative trendswere identified. The positive trend of fall and winter time series also explains the positive trend of annual time series.

As for the annual time series, also for seasonal seriesno relationship can be established between variability and trend.

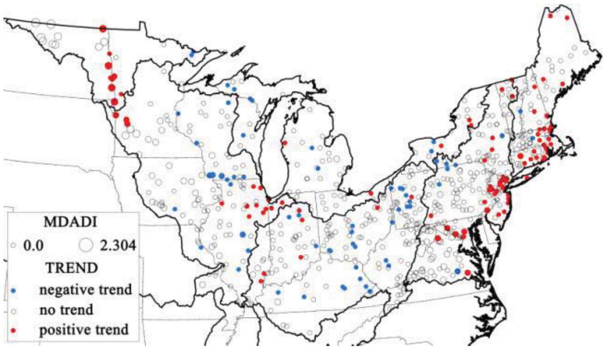

Fig. 6. Variability and trend in annual maximum (Q_{100}) of daily streamflows.

Table 3. Number of stations, and the percentage of total (669), following a trend in the annual and seasonal percentiles of daily streamflows(Significance level ≤ 0.05).

	Trend +					Trend -				
Percentile	Annual	Winter	Spring	Summer	Fall	Annual	Winter	Spring	Summer	Fall
Q_0	379 (56.7%)	399 (59.6%)	203 (30.3%)	278 (41.6%)	339(50.7%)	23 (3.40%)	9 (1.30%)	33 (4.90%)	27 (4.00%)	13 (1.90%)
Q_{50}	387 (57.8%)	262 (39.2%)	91 (13.6%)	180 (26.9%)	401(59.9%)	12 (1.80%)	10 (1.50%)	64 (9.60%)	23 (3.40%)	6 (0.90%)
Q_{mean}	278 (41.6%)	248 (37.1%)	57 (8.50%)	155 (23.2%)	423 (63.2%)	15 (2.20%)	8 (1.20%)	40 (6.00%)	15 (2.20%)	5 (0.70%)
Q_{100}	100 (14.9%)	149 (22.3%)	78 (11.7%)	85 (12.7%)	247 (36.9%)	63 (9.40%)	33 (4.90%)	74 (11.1%)	17 (2.50%)	3 (0.40%)

3.6. Trend in annual and seasonal percentiles of daily streamflows

The results of trend tests for percentilesQ_0, Q_{50} and Q_{100}, for both annual and seasonal series, are summarized in Table 3.When passing fromQ_0 to Q_{50},the stations with positive trend increase, whereasthe number decreases strongly passing from Q_{50} to Q_{100}. Only a few stations hadnegative trends, essentially for the percentile Q_{100}. For Q_0, Q_{50} and Q_{mean}, the stations with negative trends are negligible with respect to those with positive trends. When analyzing the percentile$Q_{100,}$ the stations with negative trendsare comparable with those withpositive trends instead.

SinceQ_0isthe lowest recorded daily streamflow, and thus it can be seen as a measure of the river base-flow, the analysis showed a generalized reduction of droughtsin the investigated area. Also Q_{50} (and Q_{mean}) still showeda generalizedincrease in streamflows, whereas no definitive assessment can be performed for Q_{100}because of the small number of stations with trend, although a slight reduction of streamflows can be identified.

When comparing annual and seasonal time series,it can be noted that the trend exhibited by the annual series of Q_0wasstrongly correlated to the corresponding winter and falltime series, i.e. the minimum streamflowtypically occurredwithin cold seasons. Similarly, the trend of $Q_{100}$is strongly correlated to the corresponding spring and summertime series, i.e. the maximum streamflowstypically occurred in the warm seasons.

This is also apparentwhen comparing the spatial distribution of the stations with trend in the annual and seasonal time series for different percentiles, although the figures referring to seasonal time series of Q_0, Q_{50} and Q_{100} have not been reported in the paper for the sake of brevity.

The strong seasonality of minimum and maximum streamflows has been pointed out by Lins and Slack[8].They showed thatminimum streamflows occurin fall (with the largest occurrence in September)in most stations, except for the Souris-Red-Rainy region, where the minimum streamflows typically occur in February. Similarly, most of the stations within the investigated areashowedthe maximum streamflows occurring in spring, mainly in the months of March and April.

Since a considerable increase in the annual precipitation across the U.S. has been observed[3], which can be primarily attributed to the large increase in precipitation during fall, the observed trends in low flows can be explained by an increase in fall precipitation in large partsof the basins. The precipitation has not increased at the basin scale during other seasons, thus explaining why high flows have not increased.

4. Conclusion

The study employed 70-year (from 1943 to 2012) daily stream-flow data from 669 stream gauge stations located in 23 States in the northeast United States, covering six different Water Resources Regions.

The time variability in annual and seasonal daily streamflows was assessed using the *Mean Decadal Apportionment Disorder Index* (*MDADI*) based on Shannon entropy. Four statistics were considered in the study: minimum, maximum, average and median value of daily flow for annual and seasonal time series.

Analysis pointed out that the annual series exhibited less disorder than the constituent seasonal time series for both time variability and spatial distribution: this is true for the series of Q_{50}, Q_{mean} and Q_{100}, but not for Q_0, which instead presented annual variability intermediate with respect to seasonalvariability. For all percentiles, fall showed the highest average temporal variability, whereas spring the lowest. Analysis showed again that in all cases minimum and maximum streamflowshadhigher variability than average and median streamflows.

The existence of a trendwas assessedby using *Man-Kendall test*, *Spearman's Rho test* and *Sen's slope*. The 5% two-sided confidence limit was used and it was assumed that only data series for which all tests rejected the null hypothesis followed a statistically significant trend.

A significant number of stations exhibited trends. By considering annual minimum, average and median daily streamflows, approximately 50% of stations followed trends and for almost all trendwas increasing. Only for annual maximum daily streamflow, 15% of the stations exhibit increasing trends and 10% decreasing trends. The stations with increasing trends are essentially located along the Atlantic coast and near Great Lakes and Upper Mississippi Water Regions. Similar conclusions are drawn when considering seasonal time series instead of annual data.

References

1. Clark PU, Alley RB, Pollard D. Northern hemisphere ice-sheet influences on global climate change. *Science* 1999;**286**:5442-8.
2. Milly PCD, Wetherald RT, Dunne KA, Delworth TL. Increasing risk of great floods in a changing climate. *Nature* 2002;**415**:6871-4.
3. Karl TR, Knight RW. Secular trends of precipitation amount, frequency, and intensity in the United States. *Bull Am Meteorol Soc* 1998;**79**:2-11.
4. Lettenmaier DP, Wood EW, Wallis JR. Hydro-climatological trends in the continental United States, 1948–1988. *J Climate* 1994;**7**:4-22.
5. Lins, HF, Slack, JR. Streamflow trends in the United States. *Geophys Res Lett* 1999;**26**:2-4.
6. Douglas EM, Vogel RM, Kroll CN. Trends in floods and low flows in the United States: impact of spatial correlation. *J Hydrol* 2000;**240**:90-16.
7. Small D, Islam S, Vogel R. Trends in precipitation and streamflow in the eastern U.S.: Paradox or perception? *Geophys Res Lett* 2006;**33**:3-4.
8. Lins HF, Slack JR. Seasonal and Regional Characteristics of U.S. Streamflow Trends in the United States from 1940 to 1999. *Physical Geography* 2005;**26**:6-13.
9. Singh VP. Hydrologic synthesis using entropy theory: Review. *JHydrol Eng* 2011;**16**:5-13.
10. U.S. Geological Survey. USGS Surface-Water Daily Data for the Nation. (http://waterdata.usgs.gov/nwis/dv) (Jun 2015).
11. U.S. Water Resources Council. The Nation's water resources 1975-2000, Second National Water Assessment. Washington, DC (USA): U.S. Government Printing Office; 1978.
12. De Martino G, Fontana N, Marini G, and Singh VP. Variability and Trend in Seasonal Precipitation in the Continental United States. *J Hydrol Eng* 2013;**18**:6-11.
13. Shannon CE. A mathematical theory of communication. *Bell Syst Tech J* 1948;**27**:7-45.
14. Singh VP. *Entropy Theory and its Application in Environmental and Water Engineering*. Sussex (UK): Wiley-Blackwell; 2013.
15. Singh VP. *Entropy Theory in Hydrologic Science and Engineering*. New York(USA): McGraw-Hill Education; 2015.
16. Singh VP. The use of entropy in hydrology and water resources. *Hydrol Process* 1997;**11**:6-40.
17. Rajsekhar D, Singh VP, Mishra AK. Multivariate drought index: An information theory based approach for integrated drought assessment, *J Hydrol* 2015;**526**:164-19.
18. Chiu CL. Entropy and probability concepts in hydraulics. *J Hydraul Eng* 1987;**113**:5-18.

19. Marini G, De Martino G, Fontana N, Fiorentino M, Singh VP.Entropy approach for 2D velocity distribution in open channels flow. *J Hydraul Res* 2011;**49**:6-7.
20. Singh VP, Marini G, Fontana N. Derivation of 2D power-law velocity distribution using entropy theory. *Entropy* 2013;**15(4)**:1221-11.
21. Fontana N, Marini G, De Paola F. Experimental assessment of a 2-D entropy-based model for velocity distribution in open channel flow. *Entropy* 2013;**15(3)**:988-11.
22. Mishra AK, Ozger M, and Singh VP. An entropy-based investigation into the variability of precipitation. *J Hydrol* 2009;**370:**139-16.
23. Mishra AK, Ozger M, and Singh VP. Association between uncertainties in meteorological variables and water-resources planning for the state of Texas. *J Hydrol Eng* 2011;**16**:12-16.
24. Tootle GA, and Piechota TC. Relationships between Pacific and Atlantic ocean sea surface temperatures and U.S. streamflow variability. *Water Resour Res* 2006;**42**:7-14.
25. Mann HB. Nonparametric tests against trend. *Econometrica* 1945;**13**:3-16.
26. Kendall MG. *Rank correlation methods*. London (UK): Charles Griffin; 1975.
27. Spearman C. A footrule for measuring correlation. *Br J Psychol* 1906;**2**:1-20.
28. Sen PK. Estimates of the regression coefficient based on Kendall's tau. *J Am Stat Assoc* 1968;**63**:324-11.