HYDROL24365
Decision letter
Date: 2017-04-12

Gmail **Hristos Tyralis <montchrister@gmail.com>**

HYDROL24365: Editor's decision

Journal of Hydrology <eesserver@eesmail.elsevier.com> 12 Απριλίου 2017 - 1:03 μ.μ.
Απάντηση-Προς: Journal of Hydrology <hydrol-eo@elsevier.com>
Προς: montchrister@gmail.com

Ref.: "On the long-term persistence properties of annual precipitation using a global network of instrumental measurements" (Dr. Hristos Tyralis)

Dear Dr. Tyralis,

I very much regret to have to tell you that publication entitled, "On the long-term persistence properties of annual precipitation using a global network of instrumental measurements" (Dr. Hristos Tyralis) in our journal is not recommended. An explanation for this decision is given in the attached review reports (and on https://ees.elsevier.com/hydrol/). I hope that the comments contained therein will be of use to you.

Thank you for your interest in our journal.

With kind regards,

Andras Bardossy, Dr-Ing
Editor
Journal of Hydrology
....
Important note: If a reviewer has provided a review or other materials as attachments, those items will not be in this letter. Please ensure therefore that you log on to the journal site and check if any attachments have been provided.

COMMENTS FROM EDITORS AND REVIEWERS

Associate Editor comments: This paper presents an assessment of the Hurst coefficient using global precipitation data. Two reviews of the paper were obtained. Both reviewers have significant reservations about the novelty associated with the paper as no clear new contribution is present. While the spatial prediction of the Hurst coefficient (in locations where there is no precipitation data) could have been of interest, I am not sure if the results in Figure 7 of the paper are any better than using instead a gridded rainfall product. In fact, I felt this paper may be able to make a stronger contribution were it to focus on the inability of the many grided precipitation datasets around to properly represent low-frequency variability (if that is indeed the case). I realise a fair bit of work has gone into the paper, but I cannot see the contribution as novel enough to merit publication in Journal of Hydrology. I suggest the authors attempt to address the limitations pointed
out here and resubmit their work on an alternate publication outlet. I am sorry I cannot be more positive in my assessment.

Reviewer #1: The authors investigated the annual precipitation of more than 1500 stations in North America, Europe, and Australia to investigate long term persistence. The topic and the global scope of the analysis are important, but not new as the authors themselves noted in the manuscript. The authors did not try to write explicitly the aim or the contribution of this manuscript, but from the last section of the Introduction and the "Highlights", I can say that it is the idea of building a predictive model for Hurst parameter (H), and using random forest model for this, rather than linear regression.
I appreciate the work, but I do not see a case made for a publication in the Journal of Hydrology. There are no significant findings that bring new information to the readers - no identified trends and no region-specific knowledge. The authors used a language that struck me about the random forest models performing well in predicting H values based on the geographical location. I cannot find results that support this claim. The best regression models have correlation r value of 0.5. In regression terminology, this means r-squared of 0.25, which means a model that explains only 25% of the predictand's variability. Figure 7 reveals that the model is not good. Actually, the figure is also misleading because it regresses the predicted versus "actual" values, when it was supposed to present a 45 degree line with a scatter plot. If this was done, the authors themselves would have rejected the model.
Furthermore, the entire manuscript reads like a statistical exercise, lacking physical interpretation of the results. This is really problematic as readers of the Journal will fail to derive any substantial information from such writing style. Sentences like the one on lines 454-455, as an example, leaves the reader saying …. So what? What does it mean?
Some other minor and technical issues:
The authors refer readers to the supplementary material for significant portion of the methods. This is unrealistic expectation from readers of the Journal. It is suitable for the short notes of the journals of "Nature" and "Science",

but here you can write a bit more;
Pages 6-7: Steps B to D are difficult to understand, the authors should re-read them and edit;
Line 204: What does "autocorrelation increases in H"? Does it mean as k increases, H increases?
Lines 321-322: I cannot see in Figure 5 what the authors indicated as "higher variation of H between different classes";
Lines 386-387: "… presented in the following…". Where?
Lines 418-419: The argument that "climate" is not helping for predicting H value needs more discussion. Is this happening because what was called climate in the manuscript is not actual climate but rather climate type or class? Then, definitely the location is enough to reflect the climate class, and this should be expected;
Lines 428-429: I disagree with the authors. In Figure 8 (top and bottom), climate looks more important than elevation;
Lines 464-467: How did you come up with this based on Figure 12? It is not clear;
Lines 478-482: Again, what is the physical interpretation?
Lines 496-497: Ok, so what is new here?
Lines 498-504: What is the meaning of H value of 0.56? High or low? Persistence or no persistence?

Reviewer #2: Review

The article presents an analysis of long-term persistence and trends of annual precipitation on 1535 stations globally distributed for the period 1916-2015. The authors found an average Hurst coefficient H of 0.56. The H value has some correlation with the coordinates of the stations and with mean and standard deviation of the precipitation process. Random forest and a specific random-forest algorithm (the cforest model) show a good predictive capability in predicting local values of H from covariates (Table 4 and Fig. 7). The trend in precipitation is 36 mm/100 year on average but local trends are mostly non-significant, except for snow and polar climates, where positive significant trends are higher than other categories. Results related to global distribution of the H coefficient were already known (e.g., Fatichi et al. 2012; Sun et al 2014), however this article extends the previous analyses, in the sense that search to find a correlation between H and co-variates
using random forest and linear regression models to explain H variability. Results about precipitation trends have been also published before (e.g., Hartmann et al 2013 Figure 2.28 and Tables 2.9, 2.10) and it is quite well known that precipitation changes are typically non-statistically significant due to the low signal to noise ratio (e.g., Morin 2011). The lack of a considerable change in "global precipitation" in the last 100-years is also supported by theoretical principles and climate model analyses (e.g., Allen and Ingram 2002; Allan et al 2014). Regardless, the use of station data and a well-defined period still provide in my opinion an interesting contribute and reinforce the overall message.
In short, from what I can evaluate the article is technically sound from a statistical point of view and all the analyses are properly carried out, the results are well presented and the text is properly written. However, the research sounds just as a very detailed analysis to mostly confirm what is already known in literature and it lacks a bit of novelty and scope. I have a few comments that should help to frame the article in a wider perspective. (1) It would be better to link the current article with the overall literature on precipitation changes. (2) I would suggest to stress more why the knowledge of the "long-term" persistence of a time series is important, for instance providing some reference to studies of stochastic models where long-term persistency is included or not. (3) The uncertainty in the determination of H should be emphasized, 100-years are still a quite short time period to estimate H in single station and the distribution of H reported in Fig. 2 could
be related to local differences but also to uncertainty of H. Therefore, the random forest model could simply sort out random differences rather than differences related to some process in precipitation or spatial patterns of anomalies in H. My overall interpretation of the results is that H is mostly independent of anything has been tested on the article and likely H variability is the result of estimation uncertainty rather than of underlying spatial or physical controls.

Minor Comments

Abstract. Line 11-12. I would also highlight that it should be considered in stochastic rainfall generation models.

Abstract. In general, I would spend more words to describe the main results including the global estimate of H and precipitation trend, rather than provide a long-description of methods.

Line 134-135. Using a "linear interpolation" to fill in missing values of daily precipitation is a strong approximation considering the intermittent nature of precipitation. Some stochastic model could have been used instead accounting for precipitation frequency and intensity distribution. I understand that this would have generated multiple time-series, which may not desirable for this analysis; however, the shortcoming of the approach and potential alternatives needs additional remarks.

Line 150-153. Mean precipitation above 3000 mm and Cv larger than 0.8 are physically possible, in very wet and arid places, respectively. It is not clear to me, why they need to be removed from the analysis. However, these are very few stations and do not affect the overall analysis.

Line 164. I never heard before the expression "algebraically distant", please check.

Line 211. The terms <mu>, <sigma>, H are indicated without hat also in several of the previous expressions, actually the "hat" is only used in Lines 150-153. Please check the notation.

Line 287 and Line 407-408. I would explicitly write that the "truncated normal distribution" is expected to reproduce the H-statistics but by definition cannot reproduce any correlation with other covariates.

Line 296 and Line 439-440. These introductory lines are not necessary.

Line 558. I would suggest to not closing the article with what will be done in the future.

References

Allan, R. P., Liu, C., Zahzn, M., Lavers, D. A., Koukouvagias, E., and Bodas-Salcedo, A. 2014. Physically consistent responses of the global atmospheric hydrological cycle in models and observations, Surv. Geophys., 35, 533-552, doi:10.1007/s10712-012-9213-z,

Allen, M. R., and W. J. Ingram (2002), Constraints on future changes in climate and the hydrologic cycle, Nature, 419(6903), 224-232,doi:10.1038/nature01092

Fatichi S, Ivanov VY, Caporali E (2012) Investigating Interannual Variability of Precipitation at the Global Scale: Is There a Connection with Seasonality?. Journal of Climate 25:5512-5523. doi:10.1175/JCLI-D-11-00356.1

Hartmann, D.L., A.M.G. Klein Tank, M. Rusticucci, L.V. Alexander, S. Brönnimann, Y. Charabi, F.J. Dentener, E.J. Dlugokencky, D.R. Easterling, A. Kaplan, B.J. Soden, P.W. Thorne, M. Wild and P.M. Zhai, (2013): Observations: Atmosphere and Surface. In: Climate Change 2013: The Physical Science Basis. Contribution of Working Group I to the Fifth Assessment Report of the Intergovernmental Panel on Climate Change [Stocker, T.F., D. Qin, G.-K. Plattner, M. Tignor, S.K. Allen, J. Boschung, A. Nauels, Y. Xia, V. Bex and P.M. Midgley (eds.)]. Cambridge University Press, Cambridge, United Kingdom and New York, NY, USA.

Morin, E. (2011), To know what we cannot know: Global mapping of minimal detectable absolute trends in annual precipitation, Water Resour. Res., 47, W07505, doi:10.1029/2010WR009798

Sun Q, Kong D, Miao C, Duan Q, Yang T, Ye A, Di Z, Gong W (2014) Variations in global temperature and precipitation for the period of 1948 to 2010. Environmental Monitoring and Assessment 186(9):5663-5679. doi:10.1007/s10661-014-3811-9

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Update regarding the status of the manuscript
Date: 2017-04-10

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Update regarding the status of your submission to Journal of Hydrology

1 μήνυμα

Andras Bardossy <eesserver@eesmail.elsevier.com> 10 Απριλίου 2017 - 8:36 μ.μ.
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Journal: Journal of Hydrology
Ref: HYDROL24365
Title: On the long-term persistence properties of annual precipitation using a global network of instrumental measurements

Dear Dr. Tyralis

I am pleased to inform you that the status of your submission has now progressed to: 'Required reviews complete'.

This status means that I have received the minimum number of required reviews, which I will now evaluate in order to make a decision on your paper.

If the current reviews conflict with one another or are not detailed enough, I may need to seek the opinion of another reviewer to make a fair and informed conclusion about your paper. For this reason the status of your paper may change back to 'under review' for a short period of time.

As soon as the final editor's decision can be made, you will be notified via email.

I appreciate your understanding of the time required to provide you with a thorough decision and comments on your submission.

Kind regards,

ashish sharma
Associate Editor

Journal of Hydrology

HYDROL24365

Paper

Date: 2017-02-26

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Title: On the long-term persistence properties of annual precipitation using a global network of instrumental measurements

Article Type: Research paper

Keywords: Hurst; long-term persistence; Mann-Kendall test; precipitation; random forests; trend analysis

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Abstract: The long-term persistence (LTP) is considered an inherent property of geophysical processes. Since its presence increases uncertainty, it should be used as an additional assumption when applying hypothesis tests for assessing the significance of trends. Although significant LTP has been detected in precipitation time series in several local case studies, the results cannot be generalized for every location and climatic condition. Even in global studies, the spatial coverage of the world is limited, due to the low number of stations with sufficient quantity of instrumental measurements outside Australia, Europe and North America. For the examination of the spatial behaviour of LTP in precipitation we regress the Hurst parameter estimate of mean annual precipitation instrumental data which span from 1916-2015 and cover a big area of the earth's surface on location characteristics of the instrumental data stations. Furthermore, we apply the Mann-Kendall test under the LTP assumption (MKt-LTP) to assess the significance of observed trends. To summarize the results, the LTP seems to depend mostly non-linearly to the location of the stations, while the predictive value of the regression model is good. Thus when investigating for LTP properties we recommend that the local characteristics should be considered. Additionally, the application of the MKt-LTP suggests that no significant monotonic trend appears in global precipitation.

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February 26, 2017

Dear Editor

The submitted manuscript is a continuation of the study of Iliopoulou et al. (2016) who suggest the investigation of the dependence of the Hurst parameter of annual precipitation on the climate type. Here we use random forests to find the dependence of the Hurst parameter on geographical and location features using a global network of instrumental measurements. Furthermore, we apply the Mann-Kendall test under the long-term persistence assumption to the instrumental data to investigate for possible significant linear trends.

We think that the results of the study are particularly useful to understand the Hurst-Kolmogorov behaviour of precipitation, which is still an open subject (O'Connell et al. 2015).

Kind regards,
Hristos Tyralis

Highlights

- The Hurst parameter of annual precipitation depends on the geographical location.
- The random forests is a good spatial prediction method of the Hurst parameter.
- No significant monotonic trend appears in global precipitation.

On the long-term persistence properties of annual precipitation using a global network of instrumental measurements

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Abstract: The long-term persistence (LTP) is considered an inherent property of geophysical processes. Since its presence increases uncertainty, it should be used as an additional assumption when applying hypothesis tests for assessing the significance of trends. Although significant LTP has been detected in precipitation time series in several local case studies, the results cannot be generalized for every location and climatic condition. Even in global studies, the spatial coverage of the world is limited, due to the low number of stations with sufficient quantity of instrumental measurements outside Australia, Europe and North America. For the examination of the spatial behaviour of LTP in precipitation we regress the Hurst parameter estimate of mean annual precipitation instrumental data which span from 1916-2015 and cover a big area of the earth’s surface on location characteristics of the instrumental data stations. Furthermore, we apply the Mann-Kendall test under the LTP assumption (MKt-LTP) to assess the significance of observed trends. To summarize the results, the LTP seems to depend mostly non-linearly to the location of the stations, while the predictive value of the regression model is good. Thus when investigating for LTP properties we

recommend that the local characteristics should be considered. Additionally, the application of the MKt-LTP suggests that no significant monotonic trend appears in global precipitation.

Keywords: Hurst; long-term persistence; Mann-Kendall test; precipitation; random forests; trend analysis

1. Introduction

The long-term persistence (LTP), else known in hydrological science as Hurst phenomenon, is a behaviour observed in geophysical processes in which wet years or dry years are clustered to respective long time periods (Koutsoyiannis 2002). A common practice for evaluating the presence of the LTP is to model the geophysical time series with the Hurst-Kolmogorov process (HKp) and estimate its Hurst parameter H (Koutsoyiannis 2003; Tyralis and Koutsoyiannis 2011) where high values of H indicate strong LTP.

The estimation of H is of great importance in engineering practice (Lins and Cohn 2011). As indicated by Koutsoyiannis (2006) and Koutsoyiannis and Montanari (2007) the uncertainty increases substantially when LTP is present. This has also been shown by Tyralis and Koutsoyiannis (2014). Furthermore, due to the increase in uncertainty, observed trends in data, even if they seem significant using classical statistical testing, can be insignificant under the LTP assumption as shown by Hamed (2008).

Most studies on the assessment of the magnitude of precipitation LTP using instrumental data are local (e.g. Valle et al. 2013; Liu et al. 2012; Munshi 2015). However, some studies including Fatichi et al. (2012), Sun et al. (2014), Iliopoulou et al. (2016) estimated the magnitude of the precipitation LTP from instrumental measurements in global spatial scale and argued for its weak existence although the evidence for its presence in annual precipitation records is inconclusive (O'Connell et al. 2015). Similar global studies based on dissimilar datasets include Kumar et al. (2013) who estimated the *H* parameter of Coupled Model Intercomparison Project (CMIP5) twentieth-century precipitation simulations and Bunde et al. (2013) who used instrumental measurements, climate model simulations and precipitation reconstructions to infer on the significance of LTP in precipitation.

The Mann-Kendall test is frequently used in hydrology to evaluate the significance of trends. However, the Mann-Kendall test under the LTP assumption (MKt-LTP) (Hamed 2008), in which a possible presence of LTP is considered, has been less frequently adopted. A few local case studies, in which the authors applied the Mann-Kendall test considering the presence of LTP include the investigation of precipitation (Dinpashoh et al. 2014), stream flows (Kumar et al. 2009; Khaliq et al. 2009; Ehsanzadeh and Adamowski 2010; Sagarika et al. 2014; Zamani et al. 2016) and both (Fathian et al. 2016).

The analysis of precipitation instrumental data from stations that cover spatially the globe has become a common subject in the recent literature and is supported by the increasing availability and accessibility of global data sets (Bierkens 2015) while it is an important constituent of global-scale hydrology whose emergence was highlighted by Eagleson (1986). Such studies include the analysis of extremes (Koutsoyiannis 2004; Alexander et al. 2006; Papalexiou and Koutsoyiannis 2013; Asadieh and Krakauer 2015), droughts (Nasrollahi et al. 2015), analysis of trends (van Wijngaarden and Syed 2015), the temporal concentration of precipitation (Monjo and Martin-Vide 2016) and reconstruction of past precipitation (Smith et al. 2012). Although the instrumental data need some processing to be used, they could be considered more reliable compared to climate simulations or reconstructions. However, the coverage of the earth's surface by rain gauges is not high, while it decreases considerably when the analysis demands a sufficient long time period to obtain more reliable results. In such cases, several alternative methods have been proposed including the use of satellite data (Kidd and Huffman 2011).

The spatial analysis of precipitation based on instrumental measurements can be applied in local case studies, because the areas of interest are uniformly covered by the stations. This is the case, e.g. in Blanchet et al. (2009) who study the extreme statistics of snowfall, Villarini and Smith (2010) who investigate flood peak distributions, Li et al. (2011) who study precipitation trends and Dyrrdal et al. (2016) who analyse the extreme precipitation.

In this study, we estimate the H parameter of the mean annual precipitation from instrumental data from a large part of the earth. The database used in this study (Menne et al. 2012a,b) includes stations that cover the largest part of the inhabited earth surface. However, for statistical reasons we examine stations with data, which span the hundred-year period 1916-2015 and thus the coverage decreases considerably.

The investigation of the relationship between H and locations features is suggested for further investigation in Iliopoulou et al. (2016). The results of Sun et al. (2014) indicate that H varies considerably with the location of the stations. This is also confirmed in the Figure S3 of Markonis and Koutsoyiannis (2016) albeit their results were obtained by reconstructions of past precipitation. Spatial statistical analysis cannot be applied, because the coverage of the earth's surface by the examined stations is low and strongly non-uniform. To overcome this problem an alternative approach is to regress the H parameter estimates on location characteristics of the stations, such as the elevation and the Köppen-Geiger climate class (Kottek et al. 2006). To this end, we apply both linear regression models and random forests algorithms (Breiman 2001). The latter are particularly useful to model non-linear relationships between the dependent and the predictor variables, even when the latter are correlated.

Furthermore, we assess the significance of precipitation trends by applying the MKt-LTP test along with an exploratory analysis, in which we can present the relationship between the magnitude and significance of trends and the location characteristics. Van Wijngaarden and Syed (2015) already examined the precipitation trends using nearly 1 000 stations for the time period 1700-2013. They assessed the significance of the trends using the statistical t-test at the 5% level and they concluded that "*some caution is warranted about claiming that large changes to global precipitation have occurred during the last 150 years*".

The code used for analysing the dataset is available as supplementary information online at https://figshare.com/s/d4500cc6f711c3894421. The supplementary information also contains the six html outcomes of the code, named Part 1, …, 6, the data and information about the data (in a readme.txt file in the main folder). The interested reader can use it to reproduce our analysis.

2. Data

We used daily precipitation data from the Global Historical Climatology Network (GHCN, Menne et al. 2012a,b). Time periods of precipitation records for each station differ. The length of the time series affects the bias and uncertainty related to the parameters estimation when the Maximum Likelihood Estimator (MLE) is used (Tyralis and Koutsoyiannis 2011, see also Section 3.1). Therefore, we preferred to use the common time period 1916-2015, while we discarded data out of this period, even when the instrumental data were covering a longer time period.

2.1 Station and data selection

The initial dataset included time series with missing or flagged (i.e. data of low quality for reasons explained in Menne et al., 2012a) values. We processed the dataset according to the following briefly described sequence of actions.

A. Flagged values were considered as missing values.

B. We used the values 0.34 and 0.83 to differentiate between the months. Months with a percentage of filled values higher than 0.83 (i.e. with more than 25/30 or 26/31 daily observations) are considered good, while months with a percentage of filled values less than 0.34 (i.e. equal or less than 10/30 and 10/31 daily observations) are considered of poor quality. The reason for the differentiation is that we first aggregate to the monthly time scale and then to the annual time scale. Thus even if all values in a month are missing we can fill the monthly value after the first aggregation as described in step C.

B1. Missing values within months with observed values more than 83% were filled using linear interpolation.

B2. All values within months with observed values less than 34% were considered as missing.

B3. For the rest of the months the missing values were filled using linear interpolation and then these months were considered as missing. The reason is explained in step D.

C. Missing months corresponding to steps B2 and B3 (the latter after the substitution with missing values) were filled using a seasonal Kalman filter, implemented in the R package zoo (Zeileis and Grothendieck 2005).

D. Mean monthly values for months included in both B3 and C were calculated with the mean of monthly values of steps B3 and C.

E. From the mean monthly values we obtained the mean annual values.

F. Finally we discarded annual time series if one of the following constraints was satisfied:

F1. Two or more missing years.

F2. $\hat{H} \geq 0.95$, mean annual rainfall $\hat{\mu} \geq 3000$ mm, standard deviation of annual rainfall $\hat{\sigma} \geq 750$ mm, coefficient of variation of annual rainfall $\hat{c}_{\mathrm{v}} \geq 0.8$. We set these constraints on the estimated parameters because a preliminary analysis showed that higher values were outliers.

F3. Four or more years with less than 60% of observed daily values.

The estimated parameters of the annual time series of step F2 are described in Section 3.1. The interested reader is referred to Part 3 of the Supplementary Information for more details regarding the use of selection algorithms, constraints for data inclusion and other details. We present the locations of the subset of stations, which remained after the initial procedure, in Figure 1. 1 535 stations remained, most of which are located in Australia, Europe and North America.

Data for each station include its geographic coordinates, i.e. elevation, longitude and latitude. We calculated the Cartesian coordinates of stations under the assumption of a spherical earth using eqs (1)-(3) to model the proximity of stations, which appear to be algebraically distant when considering their longitudes.

$$\mathrm{x} = R \cos(\mathrm{lat}) \cos(\mathrm{lon}) \tag{1}$$

$$\mathrm{y} = R \cos(\mathrm{lat}) \sin(\mathrm{lon}) \tag{2}$$

$$z = R \sin(\text{lat}) \quad (3)$$

R denotes the radius of the earth. The x and y axes of the Cartesian coordinate system define a plane which includes all points with zero latitude, while the z axis is perpendicular to the plane. E.g. for given lat = 0°, stations with longitudes -180° and 180° are coincident. The coincidence can be reproduced by the transformations (1)-(3).

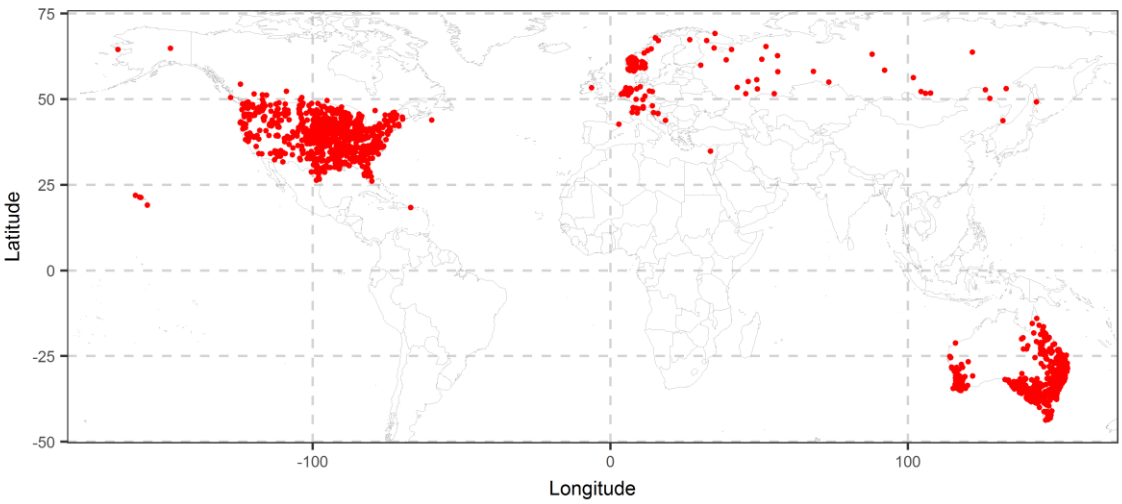

Figure 1. Map of locations for the 1 535 stations used in the analysis.

2.1.1 Grouping of stations to Köppen-Geiger climate classes

The stations are grouped based on the climate classification of Köppen-Geiger (Kottek et al. 2006). Table 1 presents the classes, whose combination gives the climatic types.

Table 1. Köppen-Geiger climate classes (Adapted from Figure 1 in Kottek et al. 2006).

Main climate		Precipitation		Temperature	
A	equatorial	W	desert	h	hot arid
B	arid	S	steppe	k	cold arid
C	warm temperate	f	fully humid	a	hot summer
D	snow	s	summer dry	b	warm summer
E	polar	w	winter dry	c	cool summer
		m	monsoonal	d	extremely continental
				F	polar frost
				T	polar tundra

We grouped the stations according to the climate type of the nearest point of the grid provided by Kottek et al. (2006). We calculated distances between stations and grid points using the Haversine ('half-versed-sine') formula as implemented in the R package geosphere (Hijmans 2016). Table 2 presents the 20 climate types of the stations. Twelve more climate types in Kottek et al. (2006) were not represented by the spatial distribution of the stations. The model calibration presented in Section 3.2 cannot be applied to the initial classification, because some climate types include a low number of stations. We regrouped the stations in the three groupings presented in Table 2. Grouping 1 included types with low number of stations together, considering their main climate and precipitation type. Grouping 2 classified stations according to their main climate. Grouping 3 is similar to that of Ragulina and Reitan (2016), who regrouped the stations according to precipitation conditions.

Table 2. Köppen-Geiger climate types of stations in Figure 1 and their regroupings.

Climate class	Number of stations	Grouping 1	Grouping 2	Grouping 3
Am	5	A	A	Am
As	4	A	A	As
Aw	9	A	A	Aw
BSh	65	BS	B	steppe
BSk	223	BS	B	steppe
BWh	21	BW	B	BWh
BWk	6	BW	B	without dry season
Cfa	419	Cfa	C	without dry season
Cfb	206	Cfb	C	without dry season
Csa	41	Ca	C	summer dry
Csb	125	Csb	C	summer dry
Cwa	5	Ca	C	winter dry
Dfa	181	Dfa	D	without dry season
Dfb	148	Dfb	D	without dry season
Dfc	52	Dfc	D	without dry season
Dsb	8	Dsw	D	summer dry
Dsc	1	Dsw	D	summer dry
Dwb	3	Dsw	D	winter dry
Dwc	4	Dsw	D	winter dry
ET	9	E	E	polar tundra

3. Methods

Here we present a minimum theoretical background of the methods, because they are established in the scientific literature.

3.1 Hurst-Kolmogorov process

We modelled the annual time series of Section 2.1 with the HKp. Let $\{\underline{x}_t\}$, t = 1,2,… be a HKp. The HKp is a three-parameter normal stationary stochastic process in discrete time. Its parameters μ, σ, H are defined by eqs (4)-(6) (Tyralis and Koutsoyiannis 2011).

$$\mu := \mathrm{E}[\underline{x}_t] \tag{4}$$

$$\sigma := (\mathrm{Var}[\underline{x}_t])^{1/2} \tag{5}$$

$$\rho_k := \mathrm{Corr}[\underline{x}_t, \mathrm{x}_{t+k}] = |k+1|^{2H} / 2 + |k-1|^{2H} / 2 - |k|^{2H}, k = 0, 1,\ldots \tag{6}$$

The parameter μ is the mean of the stochastic process and the parameter σ is its standard deviation. The parameter H represents the magnitude of LTP, i.e. the tendency of wet or dry years to be clustered in long time periods, while the autocorrelation function ρ_κ increases in H. The implementation of the Maximum Likelihood Estimator in the R package HKprocess (Tyralis 2016) was applied for estimating μ, σ and H. Furthermore, we computed the maximum likelihood estimate of the coefficient of variation, defined as:

$$c_{\mathrm{v}} = \sigma/\mu \tag{7}$$

The maximum likelihood estimate of c_{v} can be obtained from eq (7) after substitution of μ and σ with their maximum likelihood estimates due to the invariance properties of the MLE. From hereinafter estimates of μ, σ, H will be denoted without the hat symbol.

3.2 Model fitting and testing

We regressed H on combinations of other available variables related to local characteristics of the stations, i.e. their geographic coordinates, Cartesian coordinates, elevation, climate type, μ and σ. The use of geographic coordinates is more intuitive compared to Cartesian coordinates, thus we preferred to visualize the results using the former coordinate system. The regression was applied using linear regression, the random forests algorithm (Breiman 2001) as implemented in the R package randomForest (Liaw and Wiener 2002) and the cforest algorithm (Strobl et al. 2007, 2008) as implemented in the R package party (Hothorn et al. 2017).

Properties of linear models are well known, however random forests are less used in hydrological sciences. Random forests can handle non-linear interactions and highly correlated variables and have high predicting power. Furthermore, random forest variable importance measures for variable selection purposes are available (Strobl et al. 2008). Therefore, despite being black boxes they can still provide information about the relationship between the dependent and the predictor variables. In this study, we used the permutation importance, which measures the mean decrease in classification accuracy after permuting each predictor variable in the trees of the trained model, while more details can be found in the documentation of the importance function of the R package randomForest (Liaw and Wiener 2002). Yet, the random forest importance variable measures are not reliable when the predictor variables vary in their scale of measurement or their number of categories (Strobl et al. 2007). In such cases, Strobl et al. (2007) propose the use of the cforest algorithm and its respective permutation importance measure, which we also used in our study.

The three algorithms are applied through the R package caret (Kuhn 2008, Kuhn et al. 2016). We trained the three models on 80% of the sample, and we tested their performance on the rest 20%, using the Root Mean Squared Error (RMSE), Mean Absolute Error (MAE), Mean Absolute Percentage Error (MAPE) and Pearson's r metrics. H was the dependent variable, while we used a combination of spatial and location variables as predictors.

Furthermore, we applied a 5-fold cross-validation. In the 5-fold cross-validation, the original sample is randomly divided into five equal sized subsamples. The model is fitted in four subsamples and tested in the remaining one, while the procedure is repeated five times. Consequently, the randomness of the partitioning of the dataset in the 5-fold cross-validation influences the results less compared to the simple cross-validation. In the 5-fold cross-validation, we compared the performance of random forests for predicting H with the simulations of a truncated normal distribution fitted to the sample of Hs. The maximum likelihood estimates of the parameters of the truncated normal distribution in each one of the 80% folds, were used for the simulation of the other 20%. The maximum likelihood estimates were obtained using the R package tmvtnorm (Wilhelm and Manjunath 2015). The RMSE and Pearson's r metrics were used for the comparison. For more details on the application of the algorithms and the use of tuning parameters on the case of random forests and cforest, through the R package caret the interested reader is referred to Parts 4 and 5 of the Supplementary Information.

3.3 Mann-Kendall test under the long-term persistence assumption

The MKt-LTP consists of three consecutive hypothesis tests, namely **O** (Original MK test), **H** (Hurst Parameter test) and **M** (Hamed 2008). Let H_{0i} denote the null hypothesis of each test and let H_{1i} denote the alternative hypothesis, where i = **O**, **H**, **M** denotes the step of the MKt-LTP. The null hypotheses are as follows.

- $H_{0\mathbf{O}}$: No trend under the independence assumption.
- $H_{0\mathbf{H}}$: No significant LTP.
- $H_{0\mathbf{M}}$: No trend under LTP assumption.

The possible outcomes of the test are summarized by the following sequences.

- $\{H_{0\mathbf{O}}\}$: No significant trend.

- $\{H_{1\mathbf{O}}, H_{0\mathbf{H}}\}$: Significant trend exists.
- $\{H_{1\mathbf{O}}, H_{1\mathbf{H}}, H_{0\mathbf{M}}\}$: No significant trend.
- $\{H_{1\mathbf{O}}, H_{1\mathbf{H}}, H_{1\mathbf{M}}\}$: Significant trend exists.

We used the test implementation in the R package HKprocess (Tyralis 2016) with a predefined significance level $\alpha = 0.05$ for all steps. For more details on the algorithm and its implementation using the R package HKprocess the interested reader is referred to Tegos et al. (2017). Furthermore, we estimated the trends of the annual time series with the fitting of a linear model. The estimated trends were set equal to the slope of the least squares line.

4. Methodology outline

Here we describe an outline of the method and the procedure of our analysis. Firstly, we selected stations with precipitation data in the time period 1916-2015, we filled the missing data, we computed the mean annual precipitation values and discarded some stations, which did not satisfy the criteria set in Section 2.1. Then we grouped the stations in climate types (see Section 2.1.1). The record for each station includes its location (in geographic and Cartesian coordinates), its elevation, its climate type (three groupings) and mean annual precipitation time series.

We modelled the time series with HKp and we estimated its parameters μ, σ, H (Section 3.1). We regressed H on combinations of location parameters using linear regression, random forests and the cforest algorithm. The fitting of the algorithms was performed in the 80% of the 1 535 stations, while their performance was tested in the other 20%. We compared the predictions of H between the random forests and the simulation from a fitted truncated normal distribution in a 5-fold cross-validation using the RMSE and Pearson's r metrics. Furthermore, we computed variable importance measures with the application of random forests and the cforest to the full dataset (Section 3.2). The combination of the validations and the use of variable importance measures can provide reliable information despite the shortcomings of each method when used individually. Finally, we estimated the trend and its significance under the LTP assumption (Section 3.3) and we visualized the results coupled with location variables.

5. Long-term persistence analysis

In Section 5 we present the results of the analysis for the H parameter.

5.1 Overview of H

Figure 2 is the histogram of Hs. The maximum likelihood estimated values are skewed to the right with skewness equal to 0.21, while the median value is equal to 0.56. For comparison reasons and as shown in a simulation study in Part 6 of the Supplementary Information, the median of the H estimates of 100 000 simulated time series of length equal to 100 and H = 0.59 is equal to 0.56. A truncated normal distribution with support (0,1) seems to be a reasonable model for H.

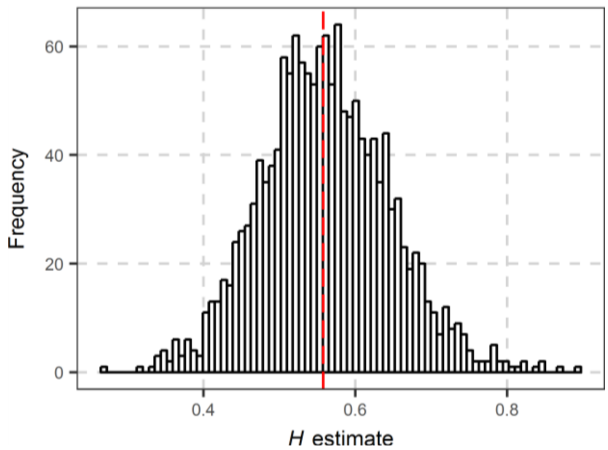

Figure 2. Histogram of H based on measurements from 1 535 stations. The median of the estimates is represented by the vertical red line and equals 0.56.

Figure 3 presents the correlations between some variables of interest. The longitude is omitted, while the inclusion of x and y coordinates as single variables would be meaningless. We observe a high correlation between μ and σ and between the absolute latitude and c_{v}. H is not highly correlated with any of the variables in Figure 3.

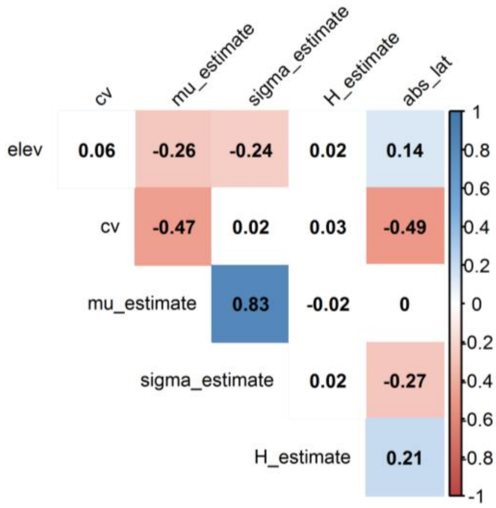

Figure 3. Correlations between numeric variables of each station based on the dataset of 1 535 stations. The variable abs_lat denotes the absolute value of the latitude.

5.2 Visualization of H coupled with the predictor variables

In Section 5.2, we visualize H coupled with the predictor variables. We present a full exploratory data analysis in the Supplementary Information, while here we present some important Figures for brevity. Figure 4 presents how H varies with the climate class of the station. Grouping 2 of Table 2 is used as the predictor variable. It seems that H does not significantly vary with grouping 2, while its values are near to the median value 0.56, computed in Section 5.1. On the other hand grouping 1 (see Table 2) in Figure 5 seems to be a better predictor, because of the higher variation of H between different climate classes.

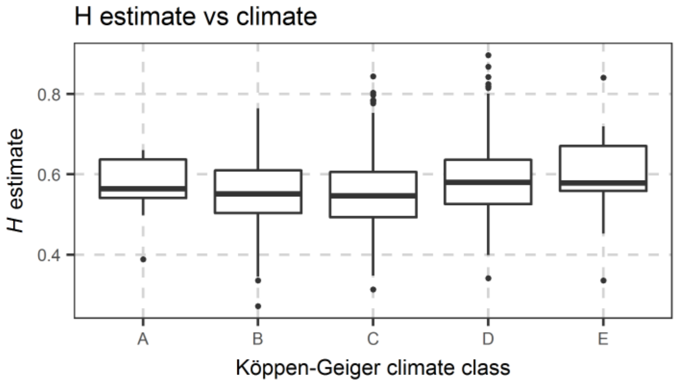

Figure 4. Boxplot of H based on the dataset of 1 535 stations conditional on the Köppen-Geiger climate class (grouping 2).

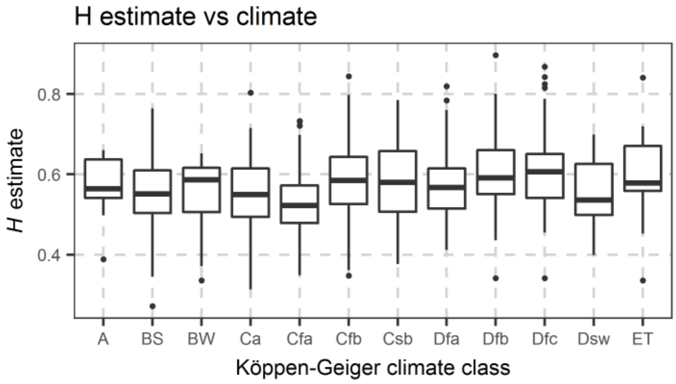

Figure 5. Boxplot of H from the dataset of 1 535 stations conditional on the Köppen-Geiger climate class (grouping 1).

In Figure 6, we observe the variation of H with the latitude. Higher H values are observed for positive latitude, however no trend prevails, while we do not observe any linear relationship between the two variables. Figure 6 also presents the relationship between H and longitude. Again, we do not observe any clear linear relationship between the two variables. Furthermore, H is not linearly related to the elevation of each station.

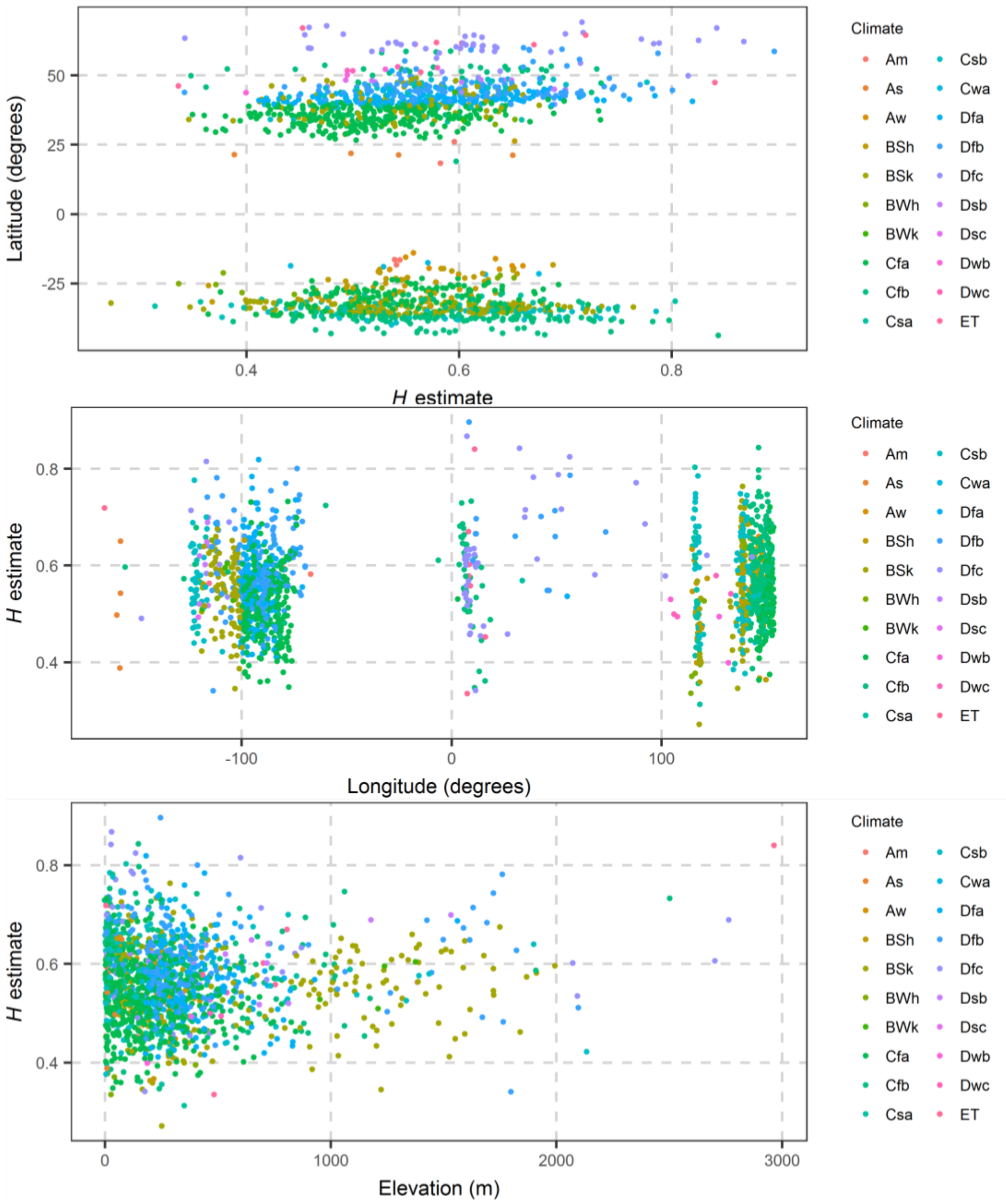

Figure 6. Scatterplot of *H* and the latitude (top), longitude (middle) and elevation (bottom) of each station. The legend presents the Köppen-Geiger climate class of each station.

5.3 Model fitting and testing

From the analysis in Section 5.2, it is apparent that a linear regression model between *H* and the location variables would not be useful. Therefore, we decided to apply a linear regression model and then compare its performance with the random forests and the cforest algorithm. We examined combinations of predictor variables as shown in Table 3. Combinations 1-11 and 16-25 include the dependence of *H* to the location of the stations. Combination 12 examines its dependence on variables, which are features of the precipitation of the station, while combinations 13-15 and 26-28 examine both location and precipitation features. We built the models of Table 3 using a stepwise regression method and in particular a forward selection approach, i.e. we started with no variables and we tested the addition of each variable using criteria such as the RMSE, the MAE, the MAPE and Pearson's r.

Table 3. Predictor variable combinations, examined in the fitting of models for the prediction of H. xyz are the Cartesian coordinates of each station. Grouping is defined in Table 2.

Combination	Predictors
1	elevation
2	grouping 1
3	grouping 2
4	grouping 3
5	x, y
6	x, y, z
7	x, y, z, grouping 1
8	x, y, z, elevation
9	x, y, z, elevation, grouping 1
10	x, y, z, elevation, grouping 2
11	x, y, z, elevation, grouping 3
12	μ, σ
13	x, y, z, elevation, grouping 1, μ, σ
14	x, y, z, elevation, grouping 2, μ, σ
15	x, y, z, elevation, grouping 3, μ, σ
16	longitude
17	latitude
18	longitude, grouping 1
19	latitude, grouping 1
20	longitude, latitude
21	longitude, latitude, grouping 1
22	longitude, latitude, elevation
23	longitude, latitude, elevation, grouping 1
24	longitude, latitude, elevation, grouping 2
25	longitude, latitude, elevation, grouping 3
26	longitude, latitude, elevation, grouping 1, μ, σ
27	longitude, latitude, elevation, grouping 2, μ, σ
28	longitude, latitude, elevation, grouping 3, μ, σ

We fitted the models on 80% of the data and we tested their performance in predicting H on the other 20%. In Table 4, we present the testing results of each model.

Combinations 1 and 3-15 for the cforest algorithm were omitted due to high computational load combined with the fact that they would not behave considerably different compared to the respective application of random forests. Random forests and the cforest had good performance while the performance of linear models was poor, indicating a strong non-linear relationship between the predictor variables and H. The cforest is more computationally intensive compared to the random forests. Firstly, we examined the dependence of H on the elevation and the climate (combinations 1-4). Grouping 1 (combination 2) was the best predictor with a similar performance for all methods. Then, we examined the dependence of H on the Cartesian coordinates combined with or without other variables (combinations 5-11, 13-15). The combination 5 (i.e. x and y coordinates) performed very good in random forests, while the inclusion of the z coordinate, the elevation and the climate type further improved the performance. Combination 11 which includes grouping 3 performed marginally better than combinations 9 and 10 which include groupings 1 and 2 respectively. Inclusion of μ and σ further improved the performance of the random forests (combinations 13-15). Secondly, we performed a similar investigation using the geographic coordinates instead of the Cartesian coordinates (combinations 16-28). The longitude and latitude (combinations 16, 17) are not good predictors. When we combine each one of them with grouping 1 (combinations 18, 19) the results are worse or similar with using grouping 1 as a single predictor. The combination 20 (i.e. longitude and latitude) performed well, while the inclusion of grouping 1 (combination 21) weakened the regression model. On the other hand, the inclusion of the elevation (combination 22) improved marginally the performance of the model. Climate type (combinations 23-25) worsened the performance, while inclusion of μ and σ (combinations 26-28) further improved the performance of the random forests. It is noteworthy that some results seem incoherent.

E.g. in the case of Cartesian coordinates, climate improves the random forests results (combinations 8-11), while for the geographic coordinates (combinations 22-25), it is the opposite. This may be explained by the slight deviations induced by the inclusion of climate. In this case, the 5-fold cross-validation presented in the following is a valid method to obtain a more reliable inference.

Table 4. Model errors in the test set for predicting H for each method and metric. Comb is the combination of predictor variables as presented in Table 3. RMSE is the Root Mean Squared Error, MAE is the Mean Absolute Error, MAPE is the Mean Absolute Percentage Error and r is the Pearson's r.

Comb	Linear model				Random forests				cforest			
	RMSE	MAE	MAPE	r	RMSE	MAE	MAPE	r	RMSE	MAE	MAPE	r
1	0.086	0.068	0.124	0.01	0.096	0.075	0.137	0.02				
2	0.084	0.068	0.124	0.24	0.084	0.068	0.124	0.24	0.084	0.068	0.124	0.25
3	0.086	0.068	0.124	0.09	0.086	0.068	0.124	0.09				
4	0.088	0.069	0.126	−0.03	0.087	0.069	0.126	−0.03				
5	0.086	0.068	0.125	0.06	0.080	0.063	0.114	0.42				
6	0.086	0.068	0.123	0.11	0.079	0.061	0.110	0.44				
7	0.084	0.068	0.123	0.26	0.079	0.061	0.111	0.43				
8	0.086	0.068	0.123	0.11	0.077	0.059	0.107	0.47				
9	0.084	0.068	0.123	0.26	0.077	0.060	0.109	0.45				
10	0.085	0.067	0.122	0.17	0.077	0.059	0.108	0.46				
11	0.086	0.068	0.124	0.13	0.076	0.059	0.106	0.48				
12	0.086	0.068	0.124	0.07	0.091	0.071	0.130	0.09				
13	0.082	0.067	0.123	0.31	0.073	0.058	0.106	0.53				
14	0.085	0.067	0.122	0.21	0.073	0.058	0.105	0.52				
15	0.086	0.068	0.124	0.14	0.073	0.058	0.105	0.53				
16	0.086	0.068	0.124	0.05	0.098	0.077	0.141	0.14	0.084	0.067	0.121	0.28
17	0.086	0.069	0.124	0.00	0.097	0.078	0.142	0.09	0.087	0.070	0.127	0.19
18	0.084	0.068	0.125	0.24	0.091	0.072	0.132	0.25	0.081	0.064	0.117	0.37
19	0.084	0.068	0.125	0.24	0.091	0.071	0.130	0.19	0.082	0.064	0.116	0.34
20	0.086	0.068	0.123	0.12	0.080	0.062	0.113	0.42	0.078	0.061	0.110	0.43
21	0.084	0.068	0.124	0.25	0.082	0.063	0.116	0.38	0.080	0.062	0.114	0.39
22	0.086	0.067	0.123	0.13	0.077	0.060	0.109	0.45	0.078	0.061	0.110	0.43
23	0.084	0.068	0.124	0.25	0.079	0.062	0.113	0.41	0.080	0.062	0.114	0.39
24	0.085	0.067	0.122	0.17	0.078	0.061	0.111	0.43	0.080	0.062	0.114	0.38
25	0.086	0.067	0.123	0.14	0.078	0.061	0.110	0.43	0.079	0.061	0.112	0.40
26	0.082	0.067	0.122	0.32	0.074	0.059	0.108	0.51	0.077	0.061	0.111	0.46
27	0.085	0.067	0.122	0.20	0.075	0.059	0.108	0.50	0.077	0.060	0.109	0.46
28	0.086	0.068	0.123	0.15	0.075	0.059	0.108	0.50	0.076	0.060	0.109	0.47

In Figure 7, we present the predicted H from the application of the trained random forests for the combination 23 to the test set. Pearson's r indicates a good prediction, while the range of predicted Hs is smaller than the range of Hs in the test set. We observe the same behaviour for the cforest algorithm in Figure 7 albeit Pearson's r is somewhat lower.

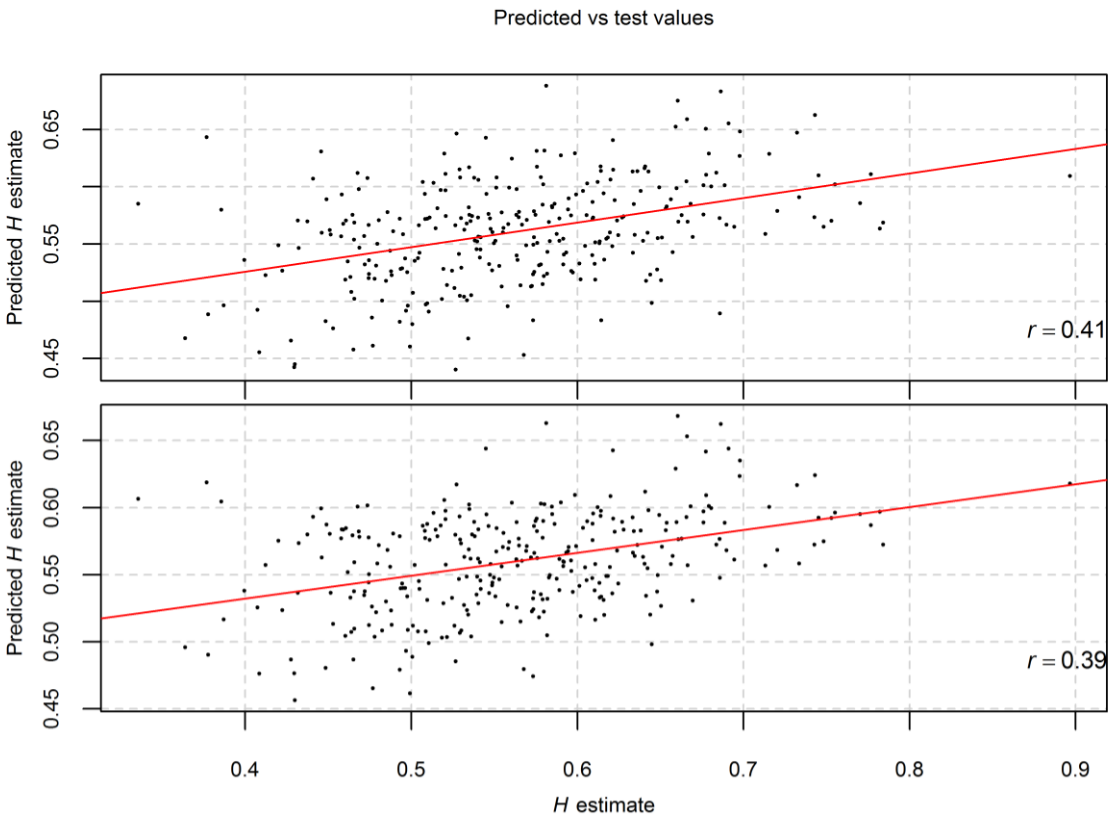

Figure 7. H of the test set in the x-axis and predicted H for the test set in the y-axis using the random forests (top) and the cforest algorithm (bottom) for the combination 23 of predictor variables defined in Table 3. r denotes Pearson's r.

In Table 5, we present the results of a 5-fold cross-validation for the prediction of H. We compare the random forests in the combinations 2, 9, 16-21, 23 of predictor variables with the truncated normal distribution. We did not examine combinations including μ and σ because if we wished to predict H in a given location based on the fitted model, their values would be unknown. The RMSE of the random forests is lower than that of the truncated normal distribution. However, it is notable albeit expected that Pearson's r is approximately 0 for the truncated normal distribution. This highlights the importance of the high predicting performance of the random forests in terms of Pearson's r. Furthermore, we note that the variation of RMSE and Pearson's r values is low for all 9 random forests cases, meaning that the algorithm is stable with respect to the choice of the fitting sample. There is a rather weak relationship between H and grouping 1 (combination 2), while there is a rather moderate relationship between H

and the longitude and latitude predictors (combination 20). The inclusion of grouping 1 to the longitude and latitude predictors (combination 21) did not improve the model compared to combination 20. However, the inclusion of grouping 1 and the elevation (combination 23) as predictor variables improved marginally the predictive performance of the fitted model. A possible explanation is that all information about H is included in the geographic location of the stations. Knowing the climate class of the stations does not add any information to that obtained by their locations.

Table 5. 5-fold cross-validation for predicting H for the random forests and the truncated normal distribution. Comb is the combination of predictor variables as presented in Table 3. Val denotes the number of the cross-validation. Two metrics were used, i.e. RMSE which is the Root Mean Squared Error and r which is the Pearson's r. The last column is equal to the mean value of the metrics.

Method	Comb	Metric	Val 1	Val 2	Val 3	Val 4	Val 5	Mean
Random forests	2	RMSE	0.079	0.079	0.080	0.086	0.083	0.082
	2	r	0.35	0.28	0.28	0.24	0.30	0.29
	9	RMSE	0.074	0.071	0.074	0.081	0.076	0.075
	9	r	0.49	0.49	0.49	0.42	0.49	0.48
	16	RMSE	0.092	0.091	0.089	0.089	0.087	0.090
	16	r	0.22	0.19	0.22	0.32	0.31	0.25
	17	RMSE	0.095	0.094	0.090	0.102	0.096	0.095
	17	r	0.15	0.10	0.19	0.07	0.12	0.12
	18	RMSE	0.082	0.084	0.083	0.089	0.080	0.084
	18	r	0.40	0.33	0.35	0.33	0.44	0.37
	19	RMSE	0.092	0.089	0.087	0.096	0.088	0.090
	19	r	0.21	0.20	0.24	0.17	0.28	0.22
	20	RMSE	0.078	0.075	0.074	0.081	0.077	0.077
	20	r	0.45	0.44	0.49	0.43	0.48	0.46
	21	RMSE	0.078	0.073	0.075	0.082	0.076	0.077
	21	r	0.44	0.47	0.48	0.42	0.49	0.46
	23	RMSE	0.074	0.072	0.073	0.082	0.077	0.076
	23	r	0.49	0.48	0.50	0.41	0.48	0.47
Truncated normal		RMSE	0.085	0.082	0.084	0.089	0.088	0.086
		r	0.01	0.01	−0.01	−0.07	−0.01	−0.01

In Figure 8, we present the variable importance for the combination 23 of predictor variables because it includes all predictor variables excluding μ and σ. The location parameters are the most important for predicting H, followed by the elevation and the climate classification. On the other hand, the cforest algorithm differs in that it estimates higher importance of the climate classification as presented in Figure 8 (bottom). This is possibly owed to the better performance of the cforest algorithm when estimating categorical variables importance.

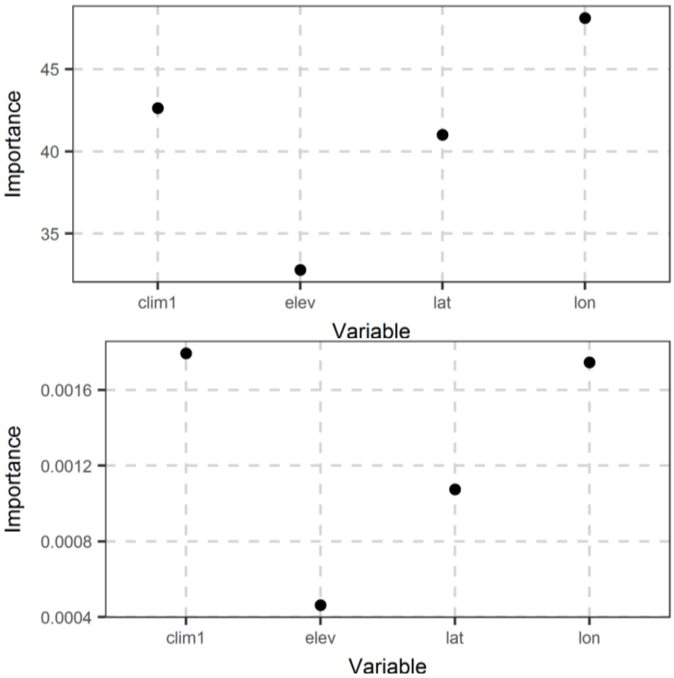

Figure 8. Variable importance for the combination 23 in Table 3 of predictor variables when random forests (top) and the cforest algorithm (bottom) is applied in the dataset of the 1 535 stations.

6. Trend analysis

In Section 6, we present the analysis on the significance of the observed trends under the LTP assumption.

6.1 Overview of trend estimates

Figure 9 is the histogram of estimated trends from the dataset of the 1 535 stations for the time period 1916-2015. The median value is equal to 0.36 mm/year, i.e. in the last 100 years we observed an increase in the annual precipitation of 36 mm. For comparison with the mean precipitation values, we note that the median annual precipitation for the 1535 stations is equal to 718 mm.

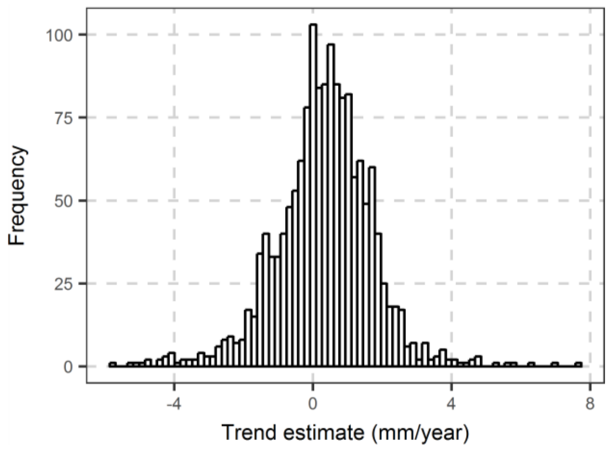

Figure 9. Histogram of trends based on the dataset of the 1 535 stations.

6.2 Visualization of trend estimates coupled with the location variables

In Section 6.2, we visualize the estimated trends as well as their significance coupled with location parameters. The full exploratory analysis is presented in the Supplementary Information, while here we present some important observations. In Figure 10, we present how the precipitation trend varies with the climate type. In all five types of grouping 2 the estimated trend is positive, while we observe a larger variation for climate type "A".

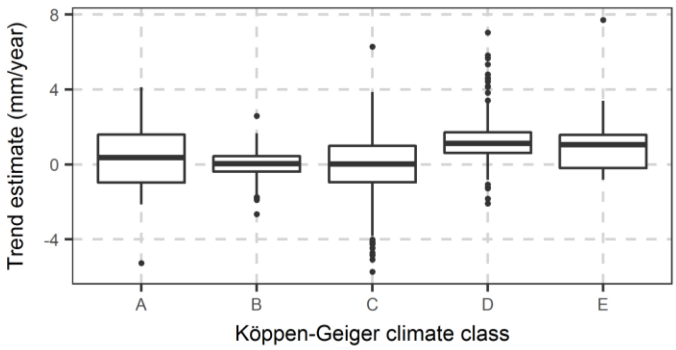

Figure 10. Boxplot of trend estimates based on the dataset of the 1 535 stations conditional on the Köppen-Geiger climate class (grouping 2).

Figure 11 presents the variation of trends conditional on grouping 3. It seems that non-significant differences are observed between different climate types.

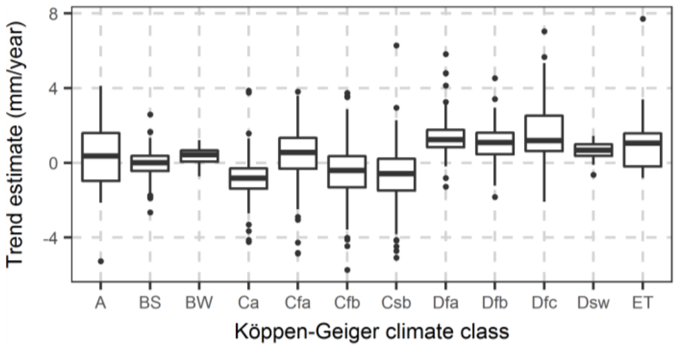

Figure 11. Boxplot of trend estimates from the dataset of the 1 535 stations conditional on the Köppen-Geiger climate class (grouping 1).

Notably, as shown in Figure 12, the mean annual precipitation seems to have been slightly increased in the Northern hemisphere and slightly decreased in the Southern hemisphere. This slight increase in the Northern hemisphere confirms the findings of van Wijngaarden and Syed (2015).

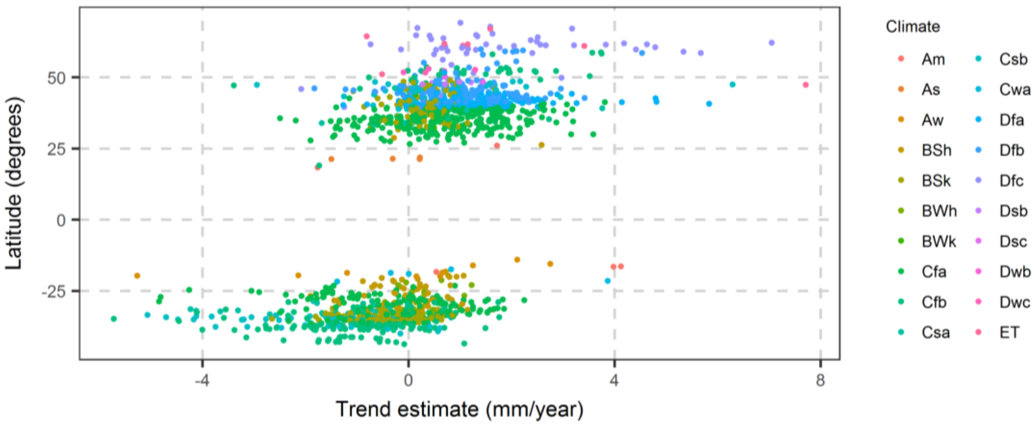

Figure 12. Scatterplot of trend estimate and the latitude of each station. The legend presents the Köppen-Geiger climate class of each station.

Figure 13 depicts the monotonicity and significance of trends per each main climate type, after application of the MKt-LTP with a predefined significance level $\alpha = 0.05$ for all steps to the mean annual precipitation time series. The absolute number of stations with main climate type D and positive significant trend is considerably higher compared to the number of stations with significant negative trend. However, the main climate types B and C are characterized by mostly significant negative trends. We cannot infer on stations with main climate types A and E because of the low number of stations. The observed patterns are also shown in a different form in Figure 13. We observe insignificant trends in approximately 50% of the stations, for main climate types A, B, C and D. However, the percentage of stations with positive significant trends is higher than the percentage of negative significant trends for main climate type D (snow) and E (polar), while the opposite is true for main climate types A, B and C (all other climates).

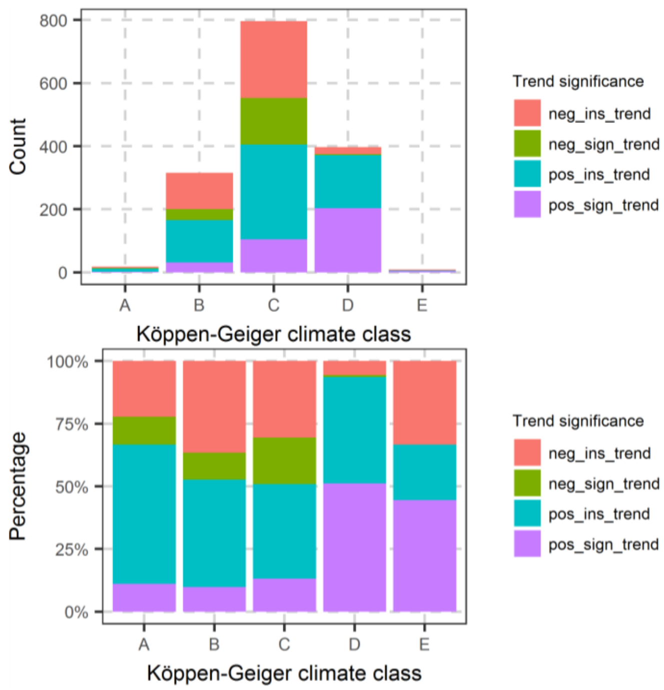

Figure 13. Number of stations with their trend significance (top) and percentages of stations for each type of trend significance (bottom) in each Köppen-Geiger climate class (grouping 2 of Table 2). Significance was estimated applying the MKt-LTP to the mean annual precipitation time series. The legend presents the sign of the trend (pos for positive and neg for negative) and its significance (sign for significant and ins for insignificant).

7. Summary, discussion and conclusions

We examined the long-term persistence properties of mean annual precipitation of 1 535 stations for the time period 1916-2015 and we tested the trends under the assumption of long-term persistence. Based on the maximum likelihood estimates of Hurst parameter H, which is a measure of long-term persistence, we found that the median value of H is equal to 0.56. This result is consistent with those of Fatichi et al. (2012), Sun et al. (2014) and Iliopoulou et al. (2016) regarding the LTP properties of the mean annual precipitation from instrumental measurements, which cover large part of the earth's land surface. Fatichi et al. (2012) estimated a median value d = 0.097, when modelling the annual precipitation with an ARFIMA(0,d,0) model (for comparison purposes: $H = d + 0.5$). Iliopoulou et al. (2016) estimated a mean H = 0.58. Sun et al. (2014) estimated H for several regions in the time period 1948-2010 covering most part of the land surface and found that the mean estimates for each region range in the interval [0.47,0.59].

In Section 5.3, we showed that the location of the station and the climate type are the most important predictor variable of H, followed by the elevation of the station. The order of importance of the three former variables depends on the algorithm. The cforest algorithm estimates that the climate type is the most important, while due to its simultaneous handling of continuous and categorical variables can be considered more reliable than the random forests in estimating the variable importance. The combinations 6 and 20 of predictor variables, which include, respectively, the Cartesian coordinates and the geographic coordinates of the stations performs well in terms of the error metrics, but most importantly, their predictions had good correlation with the tested values. This correlation cannot be achieved with fitting a distribution to the set of the H values therefore the truncated normal distribution should be used with caution when modelling H and only as a prior that needs updating in a Bayesian setting conditional on the observed precipitation of the location. The inclusion of the climate type and the elevation (combinations 9, 23) improved further, albeit little, the performance of the random forests. However, this marginal improvement means that the information obtained from the geographic location of the station already includes the information of the climate type.

The overall result is that the random forest algorithm can predict well the LTP of the mean annual precipitation, when the location characteristics are used as predictor variables while their performance is considerably better compared to the predictive ability of the simple distribution of H, particularly in terms of the correlation between the predicted and the estimated values. Therefore, the random forests can be used to predict H in locations without data or insufficient quantity of data and can serve as a substitute of spatial interpolation methods. Compared to spatial algorithms the random forests excel in combining information from distant locations through the common latitude, climate type and elevation variables, even if the spatial coverage is limited and non-uniform. The "Hurst_df.RData", which is the outcome of Part 4 of the Supplementary Information can be used by the interested reader to fit a model and predict H for other applications.

Regarding the presence of trends in the mean annual precipitation for the time period 1916-2015, it seems that the magnitude and sign of trends depend on the latitude and climate type of the station. The median of estimated trends was equal to 0.36 mm/year; however, it varies with the climate types in grouping 3 and the latitude. The MKt-LTP indicates that positive significant trends have been observed for the main climate type D (snow), while in the other climate types the percentage of stations with positive significant trends was approximately equal to that of negative significant trends, while 50% of all stations do not exhibit significant trends at all.

A limitation of our study is that the random forests algorithm can predict values only if given values of the predictor variables are within the range of the fitting set. Thus, the limited availability of data prohibits the generalization of the method to regions and Köppen-Geiger climate classes, which are not represented by the dataset. However, the random forests algorithm could provide information about the full conditional distribution of H (e.g. see Meinshausen 2006). These probabilistic predictions could be more appropriate for determining an initial prior distribution for H in a Bayesian setting compared e.g. to the uniform distribution in Tyralis et al. (2014) or to a fitted distribution in a sample of estimated H values which is independent of the location. The random forests algorithm provides additional means to examine the effect of interaction between the predictor variables and H, which could give some insights on the natural explanation of the long-term persistence in precipitation. The latter issue is of high importance in the hydrological science. To this end, non-linear transformations of the variables could be tested in addition to the exploratory data analysis presented here. Furthermore, the same fitting and testing procedure can be applied to the estimated trends and their estimated significances, to generalize the preliminary results of the trend analysis. A more thorough trend analysis will be presented in the future.

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References

Alexander LV, Zhang X, Peterson TC, Caesar J, Gleason B, Klein Tank AMG, Haylock M, Collins D, Trewin B, Rahimzadeh F, Tagipour A, Rupa Kumar K, Revadekar J, Griffiths G, Vincent L, Stephenson DB, Burn J, Aguilar E, Brunet M, Taylor M, New M, Zhai P, Rusticucci M, Vazquez-Aguirre JL (2006) Global observed changes in daily climate extremes of temperature and precipitation. Journal of Geophysical Research 111(D05109). doi:10.1029/2005JD006290

Asadieh B, Krakauer NY (2015) Global trends in extreme precipitation: climate models versus observations. Hydrology and Earth System Sciences 19(2):877–891. doi:10.5194/hess-19-877-2015

Bierkens MFP (2015) Global hydrology 2015: State, trends, and directions. Water Resources Research 51(7):4923–4947. doi:10.1002/2015WR017173

Blanchet J, Marty C, Lehning M (2009) Extreme value statistics of snowfall in the Swiss Alpine region. Water Resources Research 45(W05424). doi:10.1029/2009WR007916

Breiman L (2001) Random Forests. Machine Learning 45(1):5–32. doi:10.1023/A:1010933404324

Bunde A, Büntgen U, Ludescher J, Luterbacher J, von Storch H (2013) Is there memory in precipitation?. Nature Climate Change 3:174–175. doi:10.1038/nclimate1830

Dinpashoh Y, Mirabbasi R, Jhajharia D, Abianeh HZ, Mostafaeipour A (2014) Effect of Short-Term and Long-Term Persistence on Identification of Temporal Trends. Journal of Hydrologic Engineering 19(3):617–625. doi:10.1061/(ASCE)HE.1943-5584.0000819

Dyrrdal AV, Skaugen T, Stordal F, Førland EJ (2016) Estimating extreme areal precipitation in Norway from a gridded dataset. Hydrological Sciences Journal 61(3):483–494. doi:10.1080/02626667.2014.947289

Eagleson PS (1986) The emergence of global-scale hydrology. Water Resources Research 22(9S):6S–14S. doi:10.1029/WR022i09Sp0006S

Ehsanzadeh E, Adamowski K (2010) Trends in timing of low stream flows in Canada: impact of autocorrelation and long-term persistence. Hydrological Processes 24(8):970–980. doi:10.1002/hyp.7533

Fathian F, Dehghan Z, Bazrkar MH, Eslamian S (2016) Trends in hydrological and climatic variables affected by four variations of the Mann-Kendall approach in Urmia Lake basin, Iran. Hydrological Sciences Journal 61(5):892–904. doi:10.1080/02626667.2014.932911

Fatichi S, Ivanov VY, Caporali E (2012) Investigating Interannual Variability of Precipitation at the Global Scale: Is There a Connection with Seasonality?. Journal of Climate 25:5512–5523. doi:10.1175/JCLI-D-11-00356.1

Hamed KH (2008) Trend detection in hydrologic data: The Mann-Kendall trend test under the scaling hypothesis. Journal of Hydrology 349(3–4):350-363. doi:10.1016/j.jhydrol.2007.11.009

Hijmans RJ (2016) geosphere: Spherical Trigonometry. R package version 1.5-5. Available at:https://CRAN.R-project.org/package=geosphere

Hothorn T, Hornik K, Strobl C, Zeileis A (2017) party: A Laboratory for Recursive Partytioning. R package version 1.2-1. Available at:https://CRAN.R-project.org/package=party

Iliopoulou T, Papalexiou SM, Markonis Y, Koutsoyiannis D (2016) Revisiting long-range dependence in annual precipitation. Journal of Hydrology. doi:10.1016/j.jhydrol.2016.04.015

Khaliq MN, Ouarda TBMJ, Gachon P (2009) Identification of temporal trends in annual and seasonal low flows occurring in Canadian rivers: The effect of short- and long-term persistence. Journal of Hydrology 369(1–2):183–197. doi:10.1016/j.jhydrol.2009.02.045

Kidd C, Huffman G (2011) Global precipitation measurement. Meteorological Applications 18:334–353. doi:10.1002/met.284

Kottek M, Grieser J, Beck C, Rudolf B, Rybel F (2006) World Map of the Köppen-Geiger climate classification updated. Meteorologische Zeitschrift 15(3):259–263.doi:10.1127/0941-2948/2006/0130

Koutsoyiannis D (2002) The Hurst phenomenon and fractional Gaussian noise made easy. Hydrological Sciences Journal 47(4):573–595. doi:10.1080/02626660209492961

Koutsoyiannis D (2003) Climate change, the Hurst phenomenon, and hydrological statistics. Hydrological Sciences Journal 48(1):3–24. doi:10.1623/hysj.48.1.3.43481

Koutsoyiannis D (2004) Statistics of extremes and estimation of extreme rainfall: II. Empirical investigation of long rainfall records. Hydrological Sciences Journal 49(4):591–610. doi:10.1623/hysj.49.4.591.54424

Koutsoyiannis D (2006) Nonstationarity versus scaling in hydrology. Journal of Hydrology 324(1–4):239–254. doi:10.1016/j.jhydrol.2005.09.022

Koutsoyiannis D, Montanari A (2007) Statistical analysis of hydroclimatic time series: Uncertainty and insights. Water Resources Research 43(W05429). doi:10.1029/2006WR005592

Kuhn M (2008) Building Predictive Models in R Using the caret Package. Journal of Statistical Software 28(5):1–26. doi:10.18637/jss.v028.i05

Kuhn M, Contributions from Wing J, Weston S, Williams A, Keefer C, Engelhardt A, Cooper T, Mayer Z, Kenkel B, the R Core Team, Benesty M, Lescarbeau R, Ziem A, Scrucca L, Tang Y, Candan C (2016) caret: Classification and Regression Training. R package version 6.0-73. Available at:https://CRAN.R-project.org/package=caret

Kumar S, Merwade V, Kam J, Thurner K (2009) Streamflow trends in Indiana: Effects of long term persistence, precipitation and subsurface drains. Journal of Hydrology 374(1–2):171–183. doi:10.1016/j.jhydrol.2009.06.012

Kumar S, Merwade V, Kinter III JL, Niyogi D (2013) Evaluation of Temperature and Precipitation Trends and Long-Term Persistence in CMIP5 Twentieth-Century Climate Simulations. Journal of Climate 26:4168–4185. doi:10.1175/JCLI-D-12-00259.1

Li Q, Chen Y, Shen Y, Li X, Xu J (2011) Spatial and temporal trends of climate change in Xinjiang, China. Journal of Geographical Sciences 21(6):1007–1018. doi:10.1007/s11442-011-0896-8

Liaw A, Wiener M (2002) Classification and regression by randomForest. R News 2(3):18–22

Lins HF, Cohn TA (2011) Stationarity: Wanted Dead or Alive?. Journal of the American Water Resources Association 47(3):475–480. doi:10.1111/j.1752-1688.2011.00542.x

Liu L, Xu ZX, Huang JX (2012) Spatio-temporal variation and abrupt changes for major climate variables in the Taihu Basin, China. Stochastic Environmental Research and Risk Assessment 26(6):777–791. doi:10.1007/s00477-011-0547-8

Markonis Y, Koutsoyiannis D (2016) Scale-dependence of persistence in precipitation records. Nature Climate Change 6:399–401. doi:10.1038/nclimate2894

Meinshausen N (2006) Quantile regression forests. Journal of Machine Learning Research 7:983–999

Menne MJ, Durre I, Korzeniewski B, McNeal S, Thomas K, Yin X, Anthony S, Ray R, Vose RS, Gleason BE, Houston TG (2012a) Global Historical Climatology Network - Daily (GHCN-Daily), Version 3.22. NOAA National Climatic Data Center. doi:10.7289/V5D21VHZ [access date:2016-09-02]

Menne MJ, Durre I, Vose RS, Gleason BE, Houston TG (2012b) An overview of the Global Historical Climatology Network-Daily Database. Journal of Atmospheric and Oceanic Technology 29:897–910. doi:10.1175/JTECH-D-11-00103.1

Munshi J (2015) The Hurst Exponent of Precipitation. Available at Social Science Research Network. doi:10.2139/ssrn.2695753

Monjo R, Martin-Vide J (2016) Daily precipitation concentration around the world according to several indices. International Journal of Climatology 36(11):3828–3838. doi:10.1002/joc.4596

Nasrollahi N, AghaKouchak A, Cheng L, Damberg L, Phillips TJ, Miao C, Hsu K, Sorooshian S (2015) How well do CMIP5 climate simulations replicate historical trends and patterns of meteorological droughts?. Water Resources Research 51:2847–2864. doi:10.1002/2014WR016318

O'Connell PE, Koutsoyiannis D, Lins HF, Markonis Y, Montanari A, Cohn TA (2015) The scientific legacy of Harold Edwin Hurst (1880–1978). Hydrological Sciences Journal 61(9):1571–1590. doi:10.1080/02626667.2015.1125998

Papalexiou SM, Koutsoyiannis D (2013) Battle of extreme value distributions: A global survey on extreme daily rainfall. Water Resources Research 49:187–201. doi:10.1029/2012WR012557

Ragulina G, Reitan T (2016) Generalized Extreme Value's shape parameter and its nature for extreme precipitation using long-time series and Bayesian approach. Hydrological Sciences Journal. Accepted for publication

Sagarika S, Kalra A, Ahmad S (2014) Evaluating the effect of persistence on long-term trends and analyzing step changes in streamflows of the continental United States. Journal of Hydrology 517:36–53. doi:10.1016/j.jhydrol.2014.05.002

Smith TM, Arkin PA, Ren L, Shen SSP (2012) Improved Reconstruction of Global Precipitation since 1900. Journal of Atmospheric and Oceanic Technology 29:1505–1517. doi:10.1175/JTECH-D-12-00001.1

Strobl C, Boulesteix AL, Zeileis A, Hothorn T (2007) Bias in random forest variable importance measures: Illustrations, sources and a solution. BMC Bioinformatics 8(25). doi:10.1186/1471-2105-8-25

Strobl C, Boulesteix AL, Kneib T, Augustin T, Zeileis A (2008) Conditional Variable Importance for Random Forests. BMC Bioinformatics 9(307). doi:10.1186/1471-2105-9-307

Sun Q, Kong D, Miao C, Duan Q, Yang T, Ye A, Di Z, Gong W (2014) Variations in global temperature and precipitation for the period of 1948 to 2010. Environmental Monitoring and Assessment 186(9):5663–5679. doi:10.1007/s10661-014-3811-9

Tegos A, Tyralis H, Koutsoyiannis D, Hamed KH (2017) An R function for the estimation of trend significance under the scaling hypothesis- application in PET parametric annual time series. Open Water. Accepted for publication

Tyralis H (2016) HKprocess: Hurst-Kolmogorov Process. R package version 0.0-2. Available at:https://CRAN.R-project.org/package=HKprocess

Tyralis H, Koutsoyiannis D (2011) Simultaneous estimation of the parameters of the Hurst-Kolmogorov stochastic process. Stochastic Environmental Research & Risk Assessment 25(1):21–33. doi:10.1007/s00477-010-0408-x

Tyralis H, Koutsoyiannis D (2014) A Bayesian statistical model for deriving the predictive distribution of hydroclimatic variables. Climate Dynamics 42(11-12):2867–2883. doi:10.1007/s00382-013-1804-y

Valle MAV, García GM, Cohen IS, Oleschko LK, Corral JAR, Korvin G (2013) Spatial Variability of the Hurst Exponent for the Daily Scale Rainfall Series in the State of Zacatecas, Mexico. Journal of Applied Meteorology and Climatology 52:2771–2780. doi:10.1175/JAMC-D-13-0136.1

Villarini G, Smith JA (2010) Flood peak distributions for the eastern United States. Water Resources Research 46(W06504). doi:10.1029/2009WR008395

van Wijngaarden WA, Syed A (2015) Changes in annual precipitation over the Earth's land mass excluding Antarctica from the 18th century to 2013. Journal of Hydrology 531(Part 3):1020–1027. doi:10.1016/j.jhydrol.2015.11.006

Wilhelm S, Manjunath BG (2015) tmvtnorm: Truncated Multivariate Normal and Student t Distribution. R package version 1.4-10. Available at:https://CRAN.R-project.org/package=tmvtnorm

Zamani R, Mirabbasi R, Abdollahi S, Jhajharia D (2016) Streamflow trend analysis by considering autocorrelation structure, long-term persistence, and Hurst coefficient in a semi-arid region of Iran. Theoretical and Applied Climatology. doi:10.1007/s00704-016-1747-4

Zeileis A, Grothendieck G (2005) zoo: S3 Infrastructure for Regular and Irregular Time Series. Journal of Statistical Software 14(6):1–27. doi:10.18637/jss.v014.i06