Real time updating of the flood frequency distribution through data assimilation

Reply to the reviewers' comments

We are extremely grateful to the reviewers for their valuable comments and we would also like to thank the Editor and the Editorial Office for the assistance provided during the review process.

Reply to reviewer #1

Reviewer #1 is satisfied by the paper in the present form and provides a minor comment. He/she suggested justifying the choice of the NQT over a bivariate distribution directly inferenced on the data as he/she feels that a bivariate distribution directly inferenced from the data could provide more accurate results. Also he/she suggests quantifying the uncertainty of the proposed conditioned distributions.

Accordingly, we added the following statement to justify the choice of the method in section 3.2 in the revised version (page 7): "Among the advantages of the NQT, reviewed by Maranzano and Krzysztofowicz (2004), emerges the fact that it is free of any distributional assumption. Thus, the NQT allows one to avoid the selection of a suitable parametric model for the distribution of the considered hydrological variable."

As for quantification of uncertainty, we agree that this is an important issue that deserved to be discussed in the revised paper and therefore we included an extensive discussion in section 3.2 (pages 8 and 9) which is summarized here below.

Uncertainty in the conditioned distributions is mainly given by two sources: the first is uncertainty in the NQT, namely, uncertainty in the estimation of the marginal probability distribution of independent and dependent variables in the regression. The NQT is a non-parametric transformation and therefore its uncertainty cannot be determined quantitatively (see Maranzano and Krzytofowicz, 2004) and Montanari and Brath, 2004). We emphasize that it is advisable that NQT is estimated by using long records encompassing a wide range of possible meteorological and hydrological conditions.

The second source of uncertainty is related to the estimation of the cross-correlation coefficient between dependent and independent variables in the Gaussian domain. This uncertainty can be quantified for a given confidence level and again depends on the length of the records. We propose a procedure to estimate such uncertainty quantitatively and present an application in the revised version of the paper (Section 4.2.3, page 14 and Figure 8).

Reply to reviewer #2

Reviewer #2 is also satisfied by the paper but raises some issues and provides several comments in order to strengthen the value of the study. We offer a detailed point-by-point discussion here below where the original comments by the reviewer are copied in italics.

My main comment is that the study could benefit from adding a cross-validation of the method. The current results seem to largely be a description of the pattern found for these two rivers. Adding cross validation could illustrate how identifying this relationship can help inform flood forecasting, as well as demonstrate the utility of this method. For example, what if you select years with *anomalously high flows, omit them from the fitting procedure, and then assess how much this method improves prediction of floods in these years?*

We agree that a validation (in the revised paper we use the term leave-one-out validation instead of cross validation) in both rivers would definitely demonstrate the utility of the method regardless of the study site. This analysis has been included in the revised version. Additional paragraphs have been included in both the methodology (section 3.2, pages 8-9) and the results section (section 4.2.3, page 14). We provide here an anticipation of the results.

We removed the year with the wettest pre-flood season (1977 in the Po and 1944 in the Danube) and computed the correlation coefficients as well as their 95% confidence bands as explained in section 3.2. Then, we estimated the probability distribution for the peak flow in the flood season for that year. Figure 1 (Figure 8 in the revised manuscript) shows the unconditioned flood frequency distribution along with the updated one as well as the 95% confidence bands for the latter.

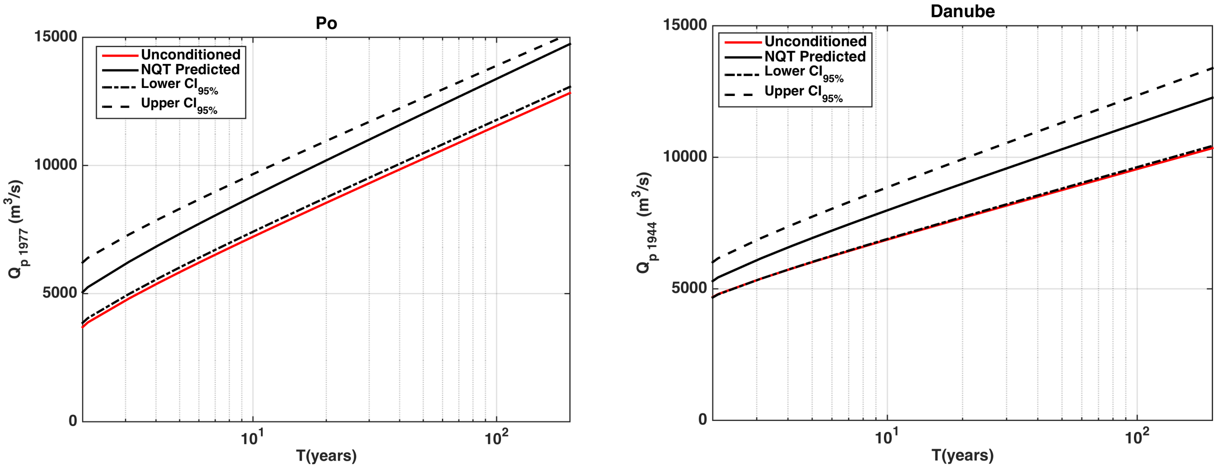

Figure 1. Leave-one-out cross validation. Unconditioned EV1 probability distribution of peak flows for the year with the wettest pre-flood season (1977 in the Po, 1944 in the upper Danube) along with conditioned distributions with related 95% confidence bands.

Also, it would be good to provide more rationale for Normal Quantile Transform as this choice likely has a big impact on results since floods generally aren't normally distributed. In addition, since meta-Gaussian models aren't commonly used it hydrology it would be helpful to add some more background on them. For example, why don't these models have fitted slope coefficients? Are these models considered linear models? Are the cross-correlation coefficients modified to ensure residuals have a mean of zero? Readers with a more traditional statistics background will likely be looking for these components of the models.

Following the reviewer's suggestion, we made reference to the literature in which a full description of the NQT can be found (Krzysztofowicz, 1997; Kelly and Krzysztofowicz, 1997). Besides, we added more references to previous applications of the NQT in hydrological studies: Krzysztofowicz and Kelly (2000); Krzysztofowicz and Herr (2001); Krzysztofowicz and Maranzano (2004a, b); Maranzano and Krzysztofowicz (2004). Also, we added the following paragraph in order to justify further the choice of the method: "Among the advantages of the NQT, reviewed by Maranzano and Krzysztofowicz (2004), emerges the fact that it is free of any distributional assumption. Thus, the NQT allows one to avoid the selection of a suitable parametric model for the distribution of the considered hydrological variable". These modifications are incorporated in section 3.2 in the revised version (pages 6-7).

+why don't these models have fitted slope coefficients?

Because they just need the standard normal distribution and the marginal probability distribution to define the NQT of the original variates.

+Are these models considered linear models?

Yes they are, as already stated in the paragraph previous to equation 2:

$$NQ_p(t) = \rho(\mathbf{NQ_m}, \mathbf{NQ_p}) NQ_m(t) + N\varepsilon(t) \quad (2)$$

+Are the cross-correlation coefficients modified to ensure residuals have a mean of zero?

Cross-correlation coefficients are not modified, but the linear model assumes that residuals (ε) are considered to be an outcome of an stochastic process, which is independent, homoscedastic, stochastically independent of $\mathbf{NQ_m}$, and normally distributed with zero mean and variance given by $1-\rho^2(\mathbf{NQ_m}, \mathbf{NQ_p})$. The evaluation based on the behavior of the residuals verifies that these conditions are met and therefore ensures that residuals have a mean of zero.

You present a review of LTP in the introduction and the abstract includes that the approach assumes flood formation is driven in part by "long term perturbations". Usually I think of long term as referring to longer than a year, but later you define "long term stress, like higher than usual rainfall lasting for several months". Can you explain a bit more about how you are defining "long term" and the link with LTP given that 9 months before flood season is the farthest back you look at correlation? And that flows before flood season only have positive correlation with during flood season for the Po river for preceding 3-4 months.

Unlike short term perturbations, that we consider to be driven by short term meteorological forcings leading to infiltration and/or saturation excess, long term perturbations may be due to higher-than-usual storage in the catchment, which may cause the presence of seasonal to interannual correlation.

We agree with the reviewer that long term persistence, which we mathematically define in the manuscript, is in principle extended to the whole past history of the process and therefore not only to the few past seasons. We are also aware that seasonal correlation is not necessarily caused by LTP, as it may also be originated by short term correlation. However, the presence of LTP makes seasonal correlation more likely and therefore we believe that a study focusing on seasonal correlation should be supported by an estimation of the possible presence of LTP. This is the reason why we believe that LTP estimation fits in our paper. We expanded this discussion in the revised version of the manuscript.

I am also curious how looking at shorter record length impacts the correlation between these variables? The data was de-trended and deseasonalized - does that mean that the correlations shown in Table 3 are stable even for subsets of the whole record you have for these rivers?

It is well known that correlations computed on short records may become unreliable. We agree that this is an important issue and therefore we included in the revised version of the paper a quantitative estimation of uncertainty for the cross-correlation coefficient (Table 3).

For our specific case, the data sets considered in our study are very long and therefore we are convinced that uncertainty in the estimation of the cross-correlation coefficient is negligible. The minimum data length to ensure meaningful conclusions depends on the statistical behaviors of the time series and, in particular, variability, as we discussed in the revised version of the paper. From a hydrological point of view, it is important that records are long and encompass a wide range of possible meteorological and hydrological conditions.

To make an experiment, we took 100 random subsets of 70 years in Po and 85 years in the Danube from the original datasets and we computed the correlation coefficients for each subset. As an example, Figure 2 represents the results for the peak flows in both rivers whose basic statistics are shown in Table 1. As we can see, we obtained a mean value similar to those obtained with the whole data sets (Table 3 in the manuscript), and the standard deviation just changes the second decimal digit.

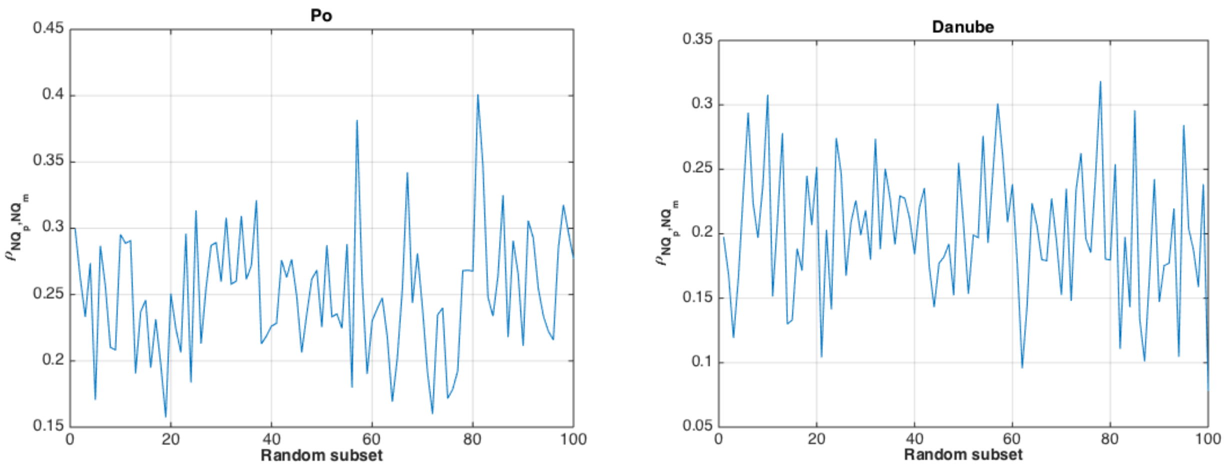

Figure 2. Pearson's cross-correlation coefficient between NQ_p and NQ_{mf} for 100 random trials of subsets in the original datasets. Flood season in Po: October-November. Flood season in Danube: May-July

Table 1. Basic statistics of the Pearson's cross-correlation coefficient between NQ_p and NQ_{mf} for 100 random trials of subsets in the original datasets.

ρ(NQ$_m$, NQ$_p$)		
	Po	**Danube**
Mean	0.25	0.20
Maximum	0.40	0.32
Minimum	0.16	0.08
Standard deviation	0.05	0.05

Finally, we would like to emphasize that data were detrended and deseasonalized for long-term memory assessments but the analysis of the statistical dependence between the peak flow in the flood season and the average flow in the pre-flood season was carried out with the original data set. Nevertheless, we also computed the correlations with the detrended and deseasonalized series and they do not change much (just the third decimal digit). We found a higher change in the correlation values (but still not a great change, just variations in the second decimal digit) when we applied the leave-one-out correlation and removed the wettest year in the pre-flood season.

More explanation of how to interpret figure 3 would be good for those of us not familiar with these types of figures. Do the regularity values come from which concentric circle the points fall on?

In order to better interpret figure 3, the following paragraph has been added at the end of section 3: "Results are shown in a circle plot where each date of occurrence of the variables analyzed in the data set are visible along the perimeter. The month of occurrence of each of the variables can be easily identified. Also, the proximity to the center of the circle of the global value indicates the regularity of the phenomenon with the highest regularity found in the perimeter of the circle."

Model residuals appear homoscedastic but what about normality? Perhaps you can mention that meta-Gaussian models don't require the usual assumption about lack of correlation in residuals, right?

Residuals were also checked for normality as this is an underlying assumption. The manuscript has been revised to make this requirement clear.

Serial correlation is assumed to be negligible, as we are regressing the annual peak flow against the average flow in the low flow season. Therefore, each year we have a pair of data and thus the above assumption is fully justified and in our opinion does not need to be checked (see also Montanari and Brath, 2004; Maranzano and Krzystofowicz, 2004).

It was unclear to me why was temperature was included in the study. Temperature patterns are discussed in the section on long term persistence, but there isn't an explanation of how temperature relates to the model or goals of the study.

Temperature as well as rainfall were included to verify whether the hypothesis of the presence of LTP is supported by data evidence in both rivers. We consider both variables to be the major drivers of river flows in both rivers, where both water mass and energy balances determine the response of the catchment. Once we demonstrated that the presence of LTP in the river flow data may be a reasonable working assumption, we use the river flow in the pre-flood season as explanatory variable. We provided in the introduction of the paper a justification for the use of river flow data as a proxy for mean areal rainfall over the catchment.

The conclusion section is quite short and could benefit from some additional discussion, perhaps something about the utility of the method for other locations and differing catchment sizes. The abstract notes "The proposed technique may allow one to reduce the uncertainty associated to the estimation of flood frequency" – could you could elaborate on this in the conclusion?

We agree with the reviewer and therefore extended the concluding remarks by discussing the applicability of the method to other cases.

Minor comments

The use of the word "significant" should be clarified (as in the abstract and p 12, line 19). Do you mean statistical significance? At what level?

We used the term "significant" to mean "noticeable". We changed the terminology to avoid confusion with terms used in statistics.

Abstract Lines 15-17: I think this would be clearer if re-organized, perhaps: "To exploit the above sensitivity to long term perturbations, a Meta-Gaussian model and a data assimilation approach is implemented for updating the flood frequency distribution a season in advance." OK

Abstract Line 20: A word is missing: I would suggest adding "which" before "occurred (ie, "which *occurred" or even "occurring" rather than just "occurred")* OK

P 2 Line 11: an "a" is missing before "long time" OK

P 2 Line 15: "associated with" more commonly used than ""associated to" OK

P 4 Line 20 Extra word "on" before "the trend" OK

P 4 Line 24 I suggest adding a comma after "As stated in the Danube River Basin Management Plan" (since it is a dependent clause) OK

P 4 Line 25 significantly rather than significant? OK

Page 9 line 18 "was" after a plural sounds strange – perhaps "We applied directional statistics. . ." OK

P 10, lines 4 This makes it sound like 0.71 is a sort of cut off. Perhaps "H values above 0.5" would be better here, reminding us that that is the cut-off of interest. Or you could say "H values of 0.71 or higher". OK

P 11 line 14 You refer to table 2 but I believe you mean table 3

Yes, we apologize for the error. It has been corrected in the revised version.

P 11 line 15 I'm not sure what you mean by "we appreciate" here.

We changed it to "always found"

P 12 line 1 Is it really "A goodness-of-fit test" or more an evaluation that model assumptions about the residuals are met?

We agree that it is an evaluation that the model assumptions about the residuals are met. We revised the text accordingly.

P 12 line 13 – again, perhaps "we find" rather than "we appreciate" OK

P 12 line 19 June is mentioned but not shown on the plots? Was that intentional?

We regret that there was an error and we meant July. It has been corrected in the revised version.

P 13 lines 1-3 The text has: "The anomaly in the low correlation coefficient in March previously explained determines an insignificant change in the estimate with respect to the unconditioned distribution." But it appears that the line corresponding to march coincides with the line corresponding to January, not to the unconditioned distribution.

Yes, we apologize for the error. It has been corrected in the revised version.

Figure 4 – I find it helpful to add a horizontal line at 0 when assessing homoscedasticity of residuals. Though I'm not sure we need to see these plots. Just describing them in the text is probably sufficient.

We regret to disagree here with the reviewer as these plots show the evaluation of the behavior of the residuals and so, including them allows us to assume that the linear model proposed can be applied to our data.

Figures 5-6 Adding a-f markers to each subplot would help with finding the plot being discussed in the text; add labels to y-axes OK

Figure 7 add to caption that the quantiles refer to flows higher than usual in the previous month. OK

Real time updating of the flood frequency distribution through data assimilation

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Abstract

We explore the memory properties of catchments for predicting the likelihood of floods basing on observations of average flows in pre-flood seasons. Our approach assumes that flood formation is driven by the superimposition of short and long term perturbations. The former is given by the short term meteorological forcing leading to infiltration and/or saturation excess, while the latter is originated by higher-than-usual storage in the catchment. To exploit the above sensitivity to long term perturbations, a Meta-Gaussian model and a data assimilation approach is implemented for updating the flood frequency distribution a season in advance. Accordingly, the peak flow in the flood season is predicted in probabilistic terms by exploiting its dependence on the average flow in the antecedent seasons. We focus on the Po River at Pontelagoscuro and the Danube river at Bratislava. We found that the shape of the flood frequency distribution is noticeably impacted by higher-than-usual flows occurring up to several months earlier. The proposed technique may allow one to reduce the uncertainty associated to the estimation of flood frequency.

1 Introduction

The physical, chemical and ecological state of processes leading to the formation and quality of river flow is characterized by persistence at several different time scales (Koutsoyiannis, 2014). In fact, anomalous conditions for such processes, such as those generated by extreme meteorological events, may produce a long-lasting impact on the river flow, depending on climatic and catchment behaviors (Lo and Famiglietti, 2010). For instance, flood generation is impacted by the initial soil moisture condition of the catchment, which may be in turn impacted by groundwater levels that are related to global catchment storage (Massari et al., 2014). Persistence can be exploited to improve river flow forecasting at seasonal-to-interannual time scale. Furthermore, persistence provides useful indications to better understand the functioning of a catchment and the dynamics of the water cycle.

Indeed, the study of persistence is one of the most classical research endeavors in hydrology, since the early works by Rippl (1883) and Hazen (1914) on the estimation of the optimal storage for reservoirs. Hurst (1951) investigated the Nile River flows while working at the design of the Aswan Dam and postulated that geophysical records may be affected by a complex form of persistence that may last for a long time (O' Connell et al., 2015). Later on, Thomas and Fiering (1962) and Yevjevich (1963) introduced autoregressive models for annual and seasonal streamflow simulation therefore stimulating the development of subsequent models of increasing complexity for simulating hydrological persistence.

Recently, the attention has been focused on long term persistence (LTP), which is associated with the Hurst-Kolmogorov behavior (Koutsoyiannis, 2011). LTP manifests itself through a power-law decay of the autocorrelation function of the process, which implies that the summation of the autocorrelation coefficients diverges to infinity (Montanari et al., 1997). LTP implies the possible presence of long term cycles (Beran, 1994), which in turn means that perturbations of hydrological processes may last for a long time, therefore providing a possible explanation for the occurrence of clusters of extreme hydrological events, such as floods and droughts (Montanari, 2012). LTP also has implications in the study of climate change, as it is connected with an enhanced natural variability of climatic processes (Koutsoyiannis and Montanari, 2007).

While LTP has been long studied, limited attempts have been made to exploit LTP in data assimilation procedures for improving streamflow forecasting. The motivation probably is that LTP is recognized to exert a noticeable impact on the river flow volume over long time scales, while its effect on the magnitude of single events is less noticeable. Nevertheless, the presence of LTP and seasonal correlation necessarily affects flood frequency, to an extent that has been poorly explored.

The present contribution aims to enhance our understanding of the persistence properties of river flows to improve seasonal river flow forecasting. By taking inspiration from the idea that the probability of extreme floods may be increased by long term stress, like higher than usual rainfall lasting for several months, the research question that we address here can be stated as follows: Can higher than usual river discharges in the previous season be associated to a higher probability of floods in the subsequent high flow season? The quantification of the effect of antecedent flows for different time lags on the occurrence of floods would help to assess how long a river remembers its past (Aguilar et al., 2016). From a technical point of view, we aim to propose a technique for updating a season in advance the flood frequency distribution estimated for a given river, through a data assimilation approach, by exploiting the information provided by river flows in the pre-flood seasons.

It is interesting to highlight that the state of a catchment, and in particular its storage, is affected by previous precipitation. Therefore, it would be reasonable to exploit the information provided by previous rainfall rather than previous flows for the sake of updating the flood frequency distribution. However, areal rainfall estimation for catchments with large extension and complex orography is affected by large uncertainty (Moulin et al., 2009). Therefore, we utilize here flows during pre-flood seasons as a proxy for catchment storage instead of rainfall. While the above assumption may be reasonable, one should consider that it may not hold when the river flows are impacted by massive regulation.

2 Study sites and data sources

We focus our attention on two large basins, namely, the Po river basin at Pontelagoscuro (Italy) and the Danube river basin at Bratislava (Slovakia). The Po River is the longest river entirely flowing in the Italian Peninsula (Fig. 1) with a catchment area of about 71000 km^2 at the delta. The average annual precipitation in the catchment is 78 km^3 in volume, of which 60% reaches the closure river cross-section at Pontelagoscuro. The hydrological behavior of the Po River is described in detail in recent studies (Zanchettin et al., 2008; Montanari, 2012; Zampieri et al., 2015). The discharge pattern at Pontelagoscuro presents a mean annual flow of about 1470 m^3s^{-1} and shows a typical pluvial regime, and thus a strong seasonality with two flood seasons in spring and autumn (Fig. 2). An intense exploitation of water resources for irrigation, hydro-power production, civil and industrial use is found in the catchment. Even though water resources management is currently sustainable on average, critical situations are experienced during drought periods (Montanari, 2012).

The upper Danube basin drains from the northern side of the Alps and the southern area of the central European Highlands into Bratislava in a 131331 km^2 catchment area where the mean annual flow is about 2053 m^3s^{-1}. The hydrological behavior of the upper Danube basin can be found in detail in the literature (Nester et al., 2011; Blöschl et al., 2013). The average annual precipitation in the catchment is 123 km^3 and the discharge pattern shows a typical alpine regime and thus a strong seasonality with one flood season in the summer (Fig. 2).

Daily discharge and monthly precipitation and temperature data for the Po and Danube river basins were analyzed in this study. The observation periods as well as descriptive statistics of the different time series are shown in Table 1. Discharge time series at Pontelagoscuro for the Po River and Bratislava for the Danube River were provided, respectively, by the Regional Agency for Environmental Protection (ARPA)— Emilia Romagna, Hydro-meteorological Office and by Global Runoff Data Center (GRDC, 2011). The series are not affected by missing values. They correspond to a time span of 90 and 107 years for Po and Danube, respectively.

The Po river is regulated by the presence of several dams as reservoirs for hydroelectricity production, which are mainly located in the Alpine region. Also, the outflow from the lakes Como, Garda, Iseo, Idro and Maggiore is regulated (Zanchettin et al., 2008). These regulations do not noticeably impact the trend and the low-frequency variability of the peak flows, while they may affect the low flows at daily and sub-daily time scale (Zampieri et al., 2015). The upper part of the Danube has been ideal for building hydropower plants and up to 59 dams are found along the river's first 1000 km. As stated in the Danube River Basin Management Plan, stretches in the very upper part of the river may present noticeably altered flows. (Maps 7a, b, c in DRBM, 2009). The effect of regulation on peak flows in Slovakia is deemed to be negligible, while low and average flows may be noticeably impacted.

Precipitation and temperature time series were calculated based on weather data sets obtained from the HISTALP project (Auer et al., 2007). Only weather stations where sufficiently long data sets are available were used (Table 1). The study period was conditioned by the availability of discharge data even though both meteorological variables were available for a longer historical period. For each study site, catchment area average precipitation and temperature time series were constructed using Thiessen polygons.

3 Methodology

In order to address the research question outlined in Section 1, namely, to verify the opportunity of updating the flood frequency distribution a season in advance by exploiting the information provided by the river flow in a given pre-flood season, we first estimate the Hurst exponent (H) for both time series, to verify whether the hypothesis of the presence of LTP is supported by data evidence. Temperature as well as rainfall were included as they are the major drivers of river flows in both rivers. Then, we turn to the analysis of the statistical dependence between the peak flow in the flood season and the average flow during the previous season, to empirically check whether updating the flood frequency distribution produces useful results.

3.1 Estimation of long term persistence

Time series with long-term memory or persistence exhibit a power-law decay of the autocorrelation function (Beran, 1994), that is:

$$\rho(k) \sim c_k k^{2H-2} \quad k \to \infty \tag{1}$$

where $\rho(k)$ is the autocorrelation function of the process at lag k, c_k is a constant and $H \in [0\ 1]$ is the Hurst exponent or the intensity of the LTP (Montanari et al., 1997). For a stationary process, H is constrained in the range [0.5,1). A value equal to 0.5 means absence of LTP; the higher the H, the higher the intensity of LTP.

In this work, H was estimated by using different heuristic methods. In detail, we applied the rescaled range (R/S) analysis, the aggregated variance method (climacogram; see Dimitriadis and Koutsyiannis, 2015), and the differenced variance method. An extended description of numerous methodologies to assess the persistence properties of time series to provide support to the possible presence of the Hurst-

Kolmogorov behavior can be found in Taqqu et al. (1995), Montanari et al. (1996, 1997, 2000) and Koutsoyiannis (2003).

A strong seasonal component in the different hydrological variables in both study time series has been reported by the literature (e.g. Montanari, 2012; Szolgayova et al., 2014; Zampieri et al, 2015). It is well known that a strong seasonality often implies the presence of periodic deterministic components in the data that can introduce a bias in LTP estimation (Montanari et al., 1997, 2000). Also, the presence of slowly decaying or increasing trends may induce a bias as well. Thus, prior to long-term memory assessments, all time series were detrended and deseasonalized. For each time series, a 366-term (for daily data) and 13-term (monthly data) moving average for a trend approximation was applied, followed by a stable seasonal filter for removing of the seasonal cycle (Brockwell et al., 2002).

3.2 Analysis of the peak flow dependence on average flows during pre-flood seasons

In order to analyze the stochastic connection between the average river flows in the antecedent seasons and the average and peak flow in the flood season, a bivariate probability distribution function was fitted. In what follows, random variables and their outcomes are identified with bold and un-bold characters, respectively. The yearly variables analyzed in this study were:

-The monthly mean flow in the given pre-flood season (independent or explanatory variable), $\mathbf{Q_m}$.

-The peak flow in the flood season or annual maximum daily flow (dependent variable), $\mathbf{Q_p}$.

-The mean daily flow in the flood season (dependent variable), $\mathbf{Q_{mf}}$.

First, the time series $Q_m(t)$, $Q_p(t)$ and $Q_{mf}(t)$ with sample size n, where n is the number of years in the observation period, are extracted from the observed datasets. Then, the Normal Quantile Transform (NQT) is applied in order to make their marginal probability distributions Gaussian, therefore obtaining the normalized observations $NQ_m(t)$ and $NQ_p(t)$ and $NQ_{mf}(t)$. NQT is fully described by Krzysztofowicz (1997) and Kelly and Krzysztofowicz (1997). Numerous applications of the NQT in hydrological studies can be found in the literature (e.g. Moran, 1970; Hosking and Wallis, 1988; Krzysztofowicz and Kelly, 2000; Krzysztofowicz and Herr, 2001; Montanari and Brath, 2004; Maranzano and Krzysztofowicz 2004; Krzysztofowicz and Maranzano 2004a, b; Montanari, 2005; Montanari and

Grossi, 2008; Bogner et al., 2012; Aguilar et al., 2016). Among the advantages of the NQT, reviewed by Maranzano and Krzysztofowicz (2004), emerges the fact that it is free of any distributional assumption. Thus, the NQT allows one to avoid the selection of a suitable parametric model for the distribution of the considered hydrological variable.

The NQT involves the following steps when we take $\mathbf{Q_m}$ as an example: (1) Sorting the sample of $Q_m(t)$ from the smallest to the largest observation, $Q_{m1}, ..., Q_{mn}$; (2) estimating the cumulative frequency FQ_{mi} by using the Weibull plotting position (Stedinger et al., 1993); (3) for each FQ_{mi} the standard normal quantile NQ_{mi} is computed as $NQ_{mi} = G^{-1}(FQ_{mi})$, with G denoting the standard normal distribution and G^{-1} its inverse, and associated with the corresponding Q_{mi}. Thus, a discrete mapping of Q_{mi} to its transformed counterpart NQ_{mi} is obtained. In order to apply the inverse of the NQT for any NQ_{mi}, linear interpolation is applied to connect the points of the discrete mapping previously obtained. Bogner et al. (2012) propose different parametric and non-parametric approaches for the extrapolation of extreme values. In this study, the region beyond the maximum and the minimum available NQ_{mi} values is covered by linear extrapolation.

Finally, a meta-Gaussian model (Kelly and Krzysztofowicz, 1997; Montanari and Brath, 2004) is fitted between the random explanatory variable and each random dependent variable in their canonical form in the Gaussian domain. In what follows, we specify the equations for the peak flow as the dependent variable. We assume: (1) stationarity and ergodicity of both $\mathbf{NQ_m}$ and $\mathbf{NQ_p}$; and (2) that the cross dependence between both $\mathbf{NQ_m}$ and $\mathbf{NQ_p}$ can be represented by the normal linear equation:

$$NQ_p(t) = \rho(\mathbf{NQ_m}, \mathbf{NQ_p}) NQ_m(t) + N\varepsilon(t) \tag{2}$$

where $\rho(\mathbf{NQ_m}, \mathbf{NQ_p})$ is the Pearson's cross-correlation coefficient between $\mathbf{NQ_m}$ and $\mathbf{NQ_p}$, and $N\varepsilon$ is an outcome of the stochastic process $\mathbf{N\Theta}$, which is independent, homoscedastic, stochastically independent of $\mathbf{NQ_m}$ and normally distributed with zero mean and variance $1-\rho^2(\mathbf{NQ_m}, \mathbf{NQ_p})$. The parameters of the bivariate probability distribution function are the mean ($\mu(\mathbf{NQ_m})=0$ and $\mu(\mathbf{NQ_p})=0$), the standard deviation ($\sigma(\mathbf{NQ_m})=1$ and $\sigma(\mathbf{NQ_p})=1$) of the normalized series, and the Pearson's cross-correlation coefficient between both normalized series, $\rho(\mathbf{NQ_m}, \mathbf{NQ_p})$. In the presence of dependence between $\mathbf{NQ_m}$ and $\mathbf{NQ_p}$, the correlation coefficient will be significantly different from zero. The bivariate Gaussian distribution implies that, for an arbitrary (observed) $NQ_m(t)$, the probability distribution function of $\mathbf{NQ_p}$ is Gaussian, with parameters (Eq. 3 and 4):

$$\mu(\mathbf{NQ_p}) = \rho(\mathbf{NQ_m}, \mathbf{NQ_p}) \cdot NQ_m(t) \quad (3)$$

$$\sigma(\mathbf{NQ_p}) = \left(1 - \rho^2(\mathbf{NQ_m}, \mathbf{NQ_p})\right)^{0.5} \quad (4)$$

Then, by taking the inverse of the NQT one can infer the updated probability distribution of $\mathbf{Q_p}$ conditioned to the observed outcome $Q_m(t)$.

In order to verify the validity of the linear model (Eq. 2), an evaluation based on the behavior of the residuals is applied. Following the graphical approach proposed by Cook and Weisberg (1994), the residual plot of $N\varepsilon(t)$ versus $\rho(\mathbf{NQ_m}, \mathbf{NQ_p}) \cdot NQ_m(t)$ should not show any systematic trend under the target model. Curve trends or fan shape trends indicate non-linear cross dependence and variability of the variance of $\mathbf{N\Theta}$, respectively (Montanari and Brath, 2004).

The same methodology was applied for the other dependent variable considered in this study, $\mathbf{Q_{mf}}$. Therefore, once the parameters of each distribution are computed, the probability distribution function of both the peak flow and the mean flow in the flood season can be updated after observing the mean flow in the considered pre-flood season.

The proposed methodology involves uncertainty in the estimated flood frequency distributions which is mainly given by two sources: the first is uncertainty in the NQT, namely, uncertainty in the estimation of the marginal probability distribution of independent and dependent variables in the regression. The second source of uncertainty is related to the estimation of the cross-correlation coefficient between dependent and independent variables in the Gaussian domain. The NQT is a non-parametric transformation and therefore its uncertainty cannot be determined quantitatively (Maranzano and Krzytofowicz, 2004; Montanari and Brath, 2004). To reduce uncertainty, it is advisable that NQT is estimated by using long records encompassing a wide range of meteorological and hydrological conditions. Uncertainty in the cross-correlation coefficient can be quantified for a given confidence level and again depends on the length of the records. A quantitative estimation of uncertainty for the cross-correlation coefficient was carried out in both study sites. Uncertainty bounds at the 95% confidence level are computed by first computing the Fisher's transformation,

$$z\left(NQ_m, NQ_p\right) = 0.5 \ln\left(\frac{1+\rho(NQ_m, NQ_p)}{1-\rho(NQ_m, NQ_p)}\right), \quad (5)$$

where the random variable **z** is approximately normally distributed with a standard deviation of:

$$\sigma(\mathbf{z}) = \sqrt{\frac{1}{n-3}} \quad (6)$$

Therefore, confidence bands for $z\left(NQ_m, NQ_p\right)$ can be computed at a given confidence level which can be converted to the confidence bands for $\rho(\mathbf{NQ_m}, \mathbf{NQ_p})$ by taking Fisher' s inverse transformation. If a negative (positive) value for the lower (upper) confidence limit is obtained for a positive (negative) estimated value of $\rho\left(\mathbf{NQ_m}, \mathbf{NQ_p}\right)$ then we reset the lower (upper) limit to 0. Finally, the limiting flood frequency distributions can be obtained for the lower and upper value of $\rho(\mathbf{NQ_m}, \mathbf{NQ_p})$.

In order to infer the actual impact of the dependence between peak flows and mean flow in the flood season with the mean flow in the pre-flood seasons, the unconditioned flood frequency distribution and the updated distributions inferred for several higher-than-average values of mean flow (e.g. 70%, 80% and 95% quantiles) in a given pre-flood season were compared. We assume that peak flows can be adequately modeled through the Extreme Value Type 1 (EV1) distribution and we present a comparison between the unconditioned peak flows frequency distribution and the updated peak flows frequency distributions.

Finally, a leave-one-out validation analysis was carried out to emulate a real-world application. We removed from the analysis the data observed in the year with the wettest pre-flood season (1977 in the Po and 1944 in the Danube) and then we estimated the probability distribution for the peak flow in the flood season for that year. Uncertainty was estimated for this application.

3.2.1 Identification of the flood season

According to previous studies in the literature, directional statistics (Mardia, 1972) represents an effective method for identifying the timing of hydrological extreme events (e.g. Castellarin et al., 2001; Cunderlik and Burn, 2002; Baratti et al., 2012). Following Bayliss and Jones (1993), the date of occurrence of an event i (e.g. maximum annual daily flow) can be transformed into a directional statistic by converting the Julian date of occurrence, Jd_i, into an angular measure, θ_i, through Eq. (7):

$$\theta_i = Jd_i \left(\frac{2\pi}{365}\right) . \qquad (7)$$

Each date of occurrence can then be written in polar coordinates by means of a vector with a unit magnitude and the direction specified by Eq. (7). Therefore, the x_p and y_p coordinates of the mean of the sample of n dates of occurrence can be computed with Eq. (8):

$$x_p = \frac{1}{n}\sum_{i=1}^{n} \cos(\theta_i) \qquad y_p = \frac{1}{n}\sum_{i=1}^{n} \sin(\theta_i) \qquad (8)$$

The direction, $\bar{\theta}$, and magnitude, r, of the mean in polar coordinates can then be obtained by Eq. (9) and Eq. (10) respectively. Equation (9) gives a measure of the mean timing of the event for the sample of dates, and can be converted back to a mean Julian date, MD, through Eq. (7). Equation (10) indicates the regularity or seasonality of the phenomenon. Values of r close to one imply a strong regularity in the dates of occurrence of the event considered. In contrast, values of r close to zero indicate a great dispersion and thus, a great inter-annual variability in the dates of occurrence of the event throughout the year.

$$\bar{\theta} = \arctan\frac{y_p}{x_p} \qquad (9)$$

$$r = \sqrt{x^2 + y^2} \qquad (10)$$

Finally, the limits of the occurrence of the phenomenon can quantitatively be identified by adding and subtracting to $\bar{\theta}$, the standard deviation in radians, σ, given by Eq. (11):

$$\sigma = \sqrt{-2\mathrm{Ln}(r)} \qquad (11)$$

We applied directional statistics to the following variables in order to identify the flood season in each study site: 1) annual maximum series of daily flows (AMD); 2) high flow events defined from frequency analysis as those events when the daily discharge exceeds the 95th percentile, Q_{95}, for longer than 15 days. Results are shown in a circle plot where each date of occurrence of the variables analyzed in the data set are visible along the perimeter. The month of occurrence of each of the variables can be easily identified. Also, the proximity to the center of the circle of the global value indicates the regularity of the phenomenon with the highest regularity found in the perimeter of the circle.

4 Results and discussion

4.1 Long term persistence estimation

The application of the heuristic methods for LTP estimation to deseasonalized and detrended time series is displayed in Table 2. H values above 0.5 were obtained for the mean daily river flows in both rivers and thus, all three heuristic methods detect the presence of noticeable LTP. The intensity of LTP seems to be more or less the same for monthly flow data. Similarly, H values in monthly temperature data of 0.64 and 0.61 in Po and Danube, respectively, suggest the presence of LTP in both records. In contrast, the estimated H values in the monthly rainfall datasets are not sensibly higher than 0.5.

In general, these results agree with previous outcomes of long term persistence studies for the daily discharge of the Po at Pontelagoscuro (Montanari, 2012) as well as with previous studies in the daily river flows in an upstream tributary of the Po (H=0.71-0.81) and in the monthly rainfall registered at certain weather stations within the watershed (Montanari et al., 1996; 1997). Also, H values of the same order of magnitude were found by Szolgayova et al. (2014) for the rainfall (H=0.43-0.50) and temperature (H=0.65-0.72) monthly time series in the upper Danube watershed at Bratislava.

4.2 Meta-Gaussian model for updating the flood frequency distribution

4.2.1 Flood season identification

Figure 3 shows the results of the directional statistics applied to the extreme events in both rivers. In the Po river, we can see a very low regularity (r≈0.1) and high dispersion (4 months) in the annual maximum daily flows (AMD in Fig. 3) due to their possible occurrence in any of the two high flow seasons, spring and autumn, as depicted in Fig. 2. The seasonality increases to r values close to 0.8 for high flow events that mostly take place in autumn as already reported in previous studies (Zanchettin et al., 2008; Montanari, 2012).

In the Danube, we find a considerable regularity in high flow events (r≈0.8) but a certain decrease in the annual maximum flows (with r values of 0.4). Nevertheless, the 2-month dispersion in the date of occurrence is lower than in the Po river and corresponds to the length of the high flow season reported in Fig.2. In view of these results we set October-November and May-July as the main flood seasons in the Po and Danube respectively.

As pre-flood season, we consider a 1-month period, which is long enough in order to reduce the effect of river regulation. We first set the month preceding the flood season (i.e., September and April for Po and Danube, respectively) as pre-flood season. Then, we repeat the analysis by making reference to the previous months, with the expectation that the statistical dependence decreases as the pre-flood season is moved back in the past.

4.2.2 Estimation of the Meta-Gaussian model

Table 3 shows the cross-correlation coefficients ρ($\mathbf{NQ_m}$,$\mathbf{NQ_p}$) and ρ($\mathbf{NQ_m}$,$\mathbf{NQ_{mf}}$), along with their confidence bands, between the normalized dependent variables ($\mathbf{NQ_p}$ and $\mathbf{NQ_{mf}}$ in both study sites) and the explanatory variable ($\mathbf{NQ_m}$) at each study site. In detail, we assumed that $\mathbf{Q_m}$ is given by the monthly mean flow in each of the 9 months preceding the floods season (from September to January in the Po river and from April to August in the antecedent year in the upper Danube). Table 3 shows that the correlation coefficient decreases as the considered pre-flood season moves backwards, as we expected. Besides, we always found noticeably higher coefficients with the mean flow in the flood season (**ρ(**$\mathbf{NQ_m}$**,** $\mathbf{NQ_{mf}}$**)**), than with the annual maximum daily flows (**ρ(**$\mathbf{NQ_m}$**,** $\mathbf{NQ_p}$**)**) in both rivers. For example, a cross-correlation coefficient of 0.24 was obtained between $\mathbf{NQ_p}$ and $\mathbf{NQ_m}$ in the Po when the pre-flood season considered is September, compared to 0.39 between $\mathbf{NQ_{mf}}$ and the same explanatory variable, $\mathbf{NQ_m}$. Moreover, a continuous decreasing cross-correlation coefficient is found as we move further apart the flood season and negative correlation in the Po river appears from May-June backwards.

The only anomalous correlation is found when considering the $\mathbf{Q_m}$ in March as the explanatory variable for both dependent variables in the Danube. This month corresponds with both the peak in the snowmelt annual cycle in the catchment (Zampieri et al., 2015) and the steepest rising slope in the hydrograph (Fig. 2). Therefore, the use of monthly mean flow might not be representative given the high variability in the daily flows along this month and the complexity of the processes that are affecting the streamflow (complex contribution from subsurface flow or from the runoff generated from snowmelt/precipitation).

An evaluation was carried out for the Meta-Gaussian model by using residuals plots (Montanari and Brath, 2004). Fig. 4 shows the residuals for a time span of 4-months backwards the flood season at each study site. The residuals look homoscedastic, therefore confirming that the model assumptions about the residuals behavior are justified.

4.2.3 Flood frequency distribution updating

In order to decipher the technical benefit that can be gained by updating the flood frequency distribution through the proposed data assimilation procedure, we assumed that above average river flows are observed in the month preceding the flood season and then applied the Meta-Gaussian model to estimate the updated probability distribution. In detail, we assume that, in average, monthly flow corresponding to the 70%, 80% and 95% quantile is observed in September for the Po River and April for the Danube River.

Fig. 5 and 6 show the unconditioned and updated probability density functions (pdf) of the normalized peak flow (i.e., the peak flow transformed to the canonical Gaussian distribution). As one would expect, the results show that the higher the cross-correlation value, the lower the variability in the distribution of the normalized dependent variable and the higher the mean value. For example, in the Po River for the occurrence of the 95th quantile value in the normalized mean flow in September, the pdf is centered around a mean vaue of 0.4 and presents a standard deviation of 0.97 (Fig. 5). In contrast, if one attempts to estimate the probability distribution of $\mathbf{NQ_p}$ conditioned to the occurrence of the 95th quantile of the normalized mean flow in July, no noticeable change is found in the estimate with respect to the unconditioned distribution. In fact, the resulting probability density function (pdf) for $\mathbf{NQ_p}$ is centered around a mean value of 0.09 with a standard deviation of 0.998. The same behavior is found in the probability distribution of the other dependent variable in its normalized form, $\mathbf{NQ_{mf}}$, where the higher correlation coefficients (Table 3) determine even a greater displacement with respect to the unconditioned distribution. In fact, the pdf of $\mathbf{NQ_{mf}}$ conditioned to the occurrence of the 95th quantile value in the normalized mean flow in September is centered around a mean vaue of 0.64 and presents a standard deviation of 0.92 (Fig. 5).

In the upper Danube a similar scheme is found with the mean of the probability distribution of $\mathbf{NQ_{p}}$ and $\mathbf{NQ_{mf}}$ conditioned to the occurrence of the 95th quantile of the normalized mean flow in April, displaced to 0.32 and 0.82 respectively (Fig. 6 and Table 3).

Figure 7 shows the comparison between the unconditioned flood frequency distribution and the updated distributions in the untransformed domain when the flow in the previous month (September for the Po River, April for the Danube River) is higher than usual (70%, 80% and 95% quantile). For example, in the Po river, the unconditioned flood for a return period of 200 years, which results equal to 12507 m^3s^{-1}, increases up to 13790 m^3s^{-1} (about 10% increase) when the mean flow in September corresponds to its 95% quantile. Similarly, in the upper Danube the unconditioned peak flow for a return period of 200 years, 10075 m^3s^{-1}, increases up to 10861 m^3s^{-1} (about 8% increase) when the mean flow in April corresponds to its 95% quantile. The differences show that the average flow during the pre-flood seasons may indeed provide useful indications to update the flood frequency distribution.

After removing from the analysis the observations of the years 1977 for the Po River and 1944 for the Danube River, which are the previous flood season wettest years in record, an emulation of a one-month-ahead real time prediction of the probability distribution of the flood flows in the next flood season was developed, along with uncertainty estimation as described in Section 3.2. Figure 8 shows, for both Po and Danube rivers, the unconditioned flood frequency distribution along with the updated one. 95% confidence bands for the latter are also shown. It can be seen that the proposed procedure allows one to obtain an effective update in real world applications.

5 Conclusions

The analysis of the observed mean daily flow values suggests the existence of LTP in both study sites with H values above 0.71. Such persistence is exploited to improve streamflow forecasting in the flood season in terms of the mean monthly flow of the pre-flood seasons. To this end, we automatically detect the flood season through directional statistics and we fit a bivariate Gaussian distribution function to model the above dependence. A 10% and 8% increase in the 200-yr return period peak flows are found in the Po and Danube, respectively, when the average flows during the previous month corresponds to its 95% quantile. The above results show that the Meta-Gaussian model applied to the streamflow records can be used for updating a season in advance the flood frequency distribution estimated for a given river, through a data assimilation approach by using the mean monthly flow of the pre-flood seasons.

The methodology herein proposed can be applied to any other study site once the parameters of the Meta-Gaussian model confirm the presence of the above stochastic dependence. Like in any time series analysis method, records that encompass a wide range of meteorological and hydrological conditions should be used to minimize uncertainty, which is in this case related to the estimation of the correlation coefficient and standardization of the regression variables. Finally, other explanatory variables (e.g. rainfall, snowmelt, etc.) can be incorporated to profit from additional stochastic dependence among peak flows and the state of the catchment and external forcings.

The findings presented in this paper highlight that river memory has an impact on flood formation and should then be properly considered for real time management of flood risk mitigation and resilience of societal settings to floods. The procedure herein described can provide useful information in those cases where the memory of the catchment is supposed to persist for a long time. These conditions may occur when the precipitation-runoff transformation is characterized by a slow development. Memory is frequently found to be related to the storage capacity of the catchment and the complexity of the river network. Therefore, they may be indicators of potential useful results from the proposed approach.

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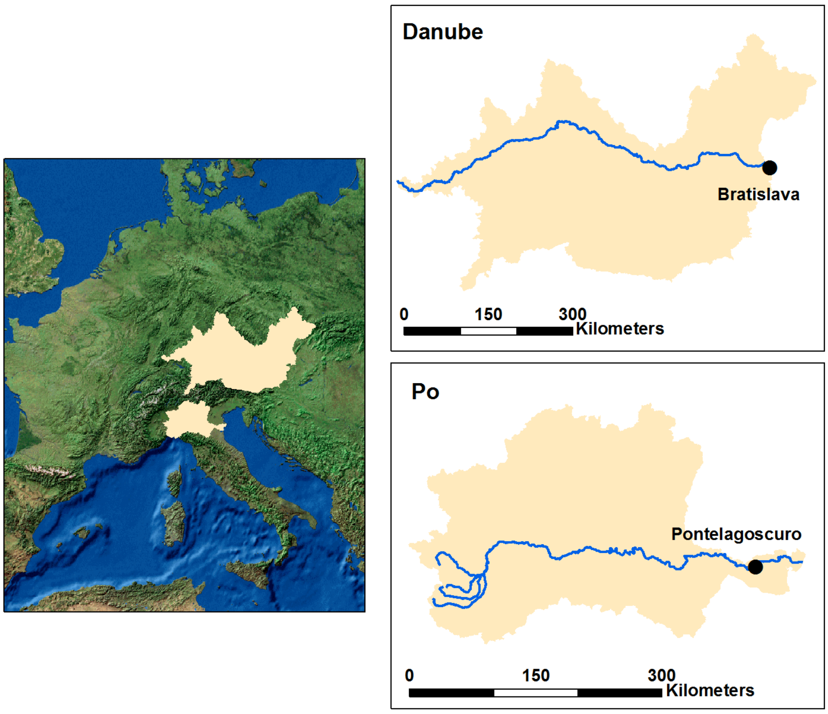

Figure 1: Study sites. Danube river basin at Bratislava and Po river basin at Pontelagoscuro.

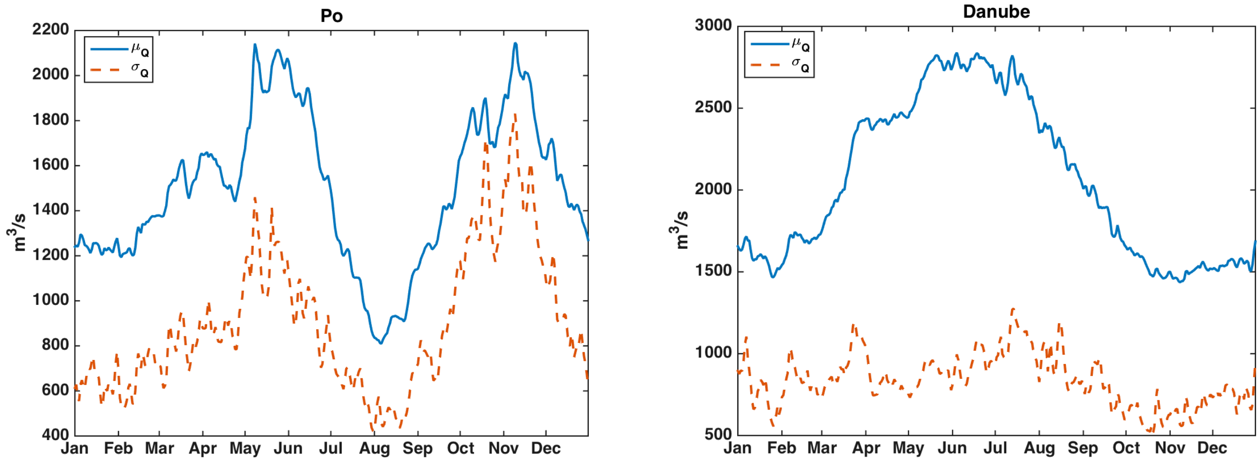

Figure 2: Daily mean value μ_Q (m^3s^{-1}) and daily standard deviation σ_Q (m^3s^{-1}) of the daily flows in the observation periods: 1920-2009 in the Po at Pontelagoscuro, 1901-2007 in the Danube at Bratislava

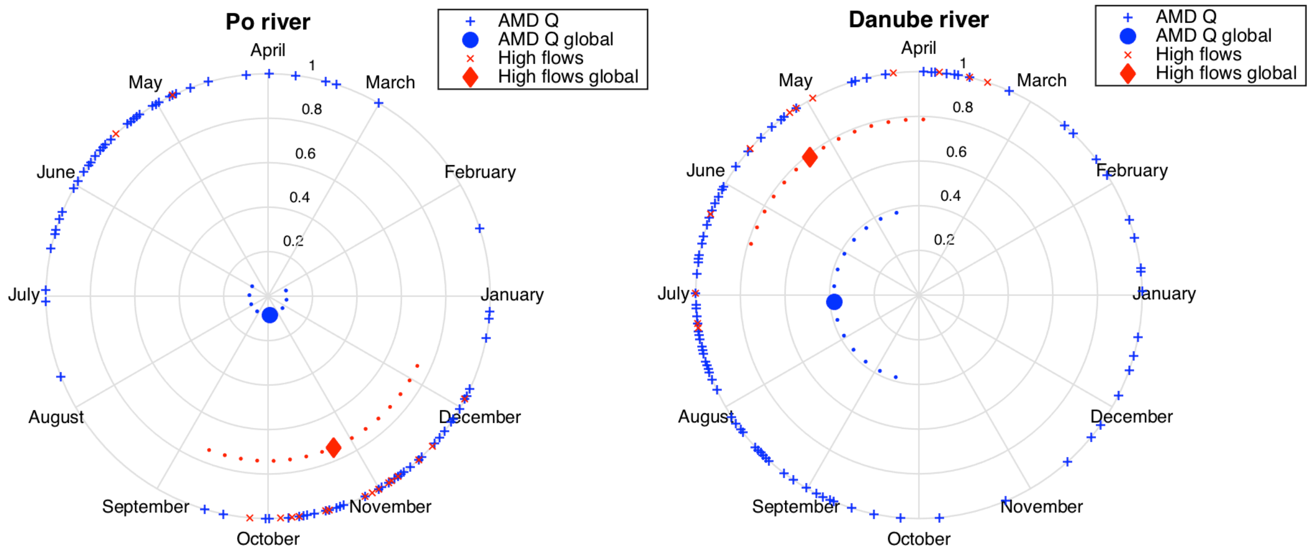

Figure 3. Seasonality space representation of the annual maximum daily flows (AMD) and high flow events. Dots around the global value indicate the dispersion.

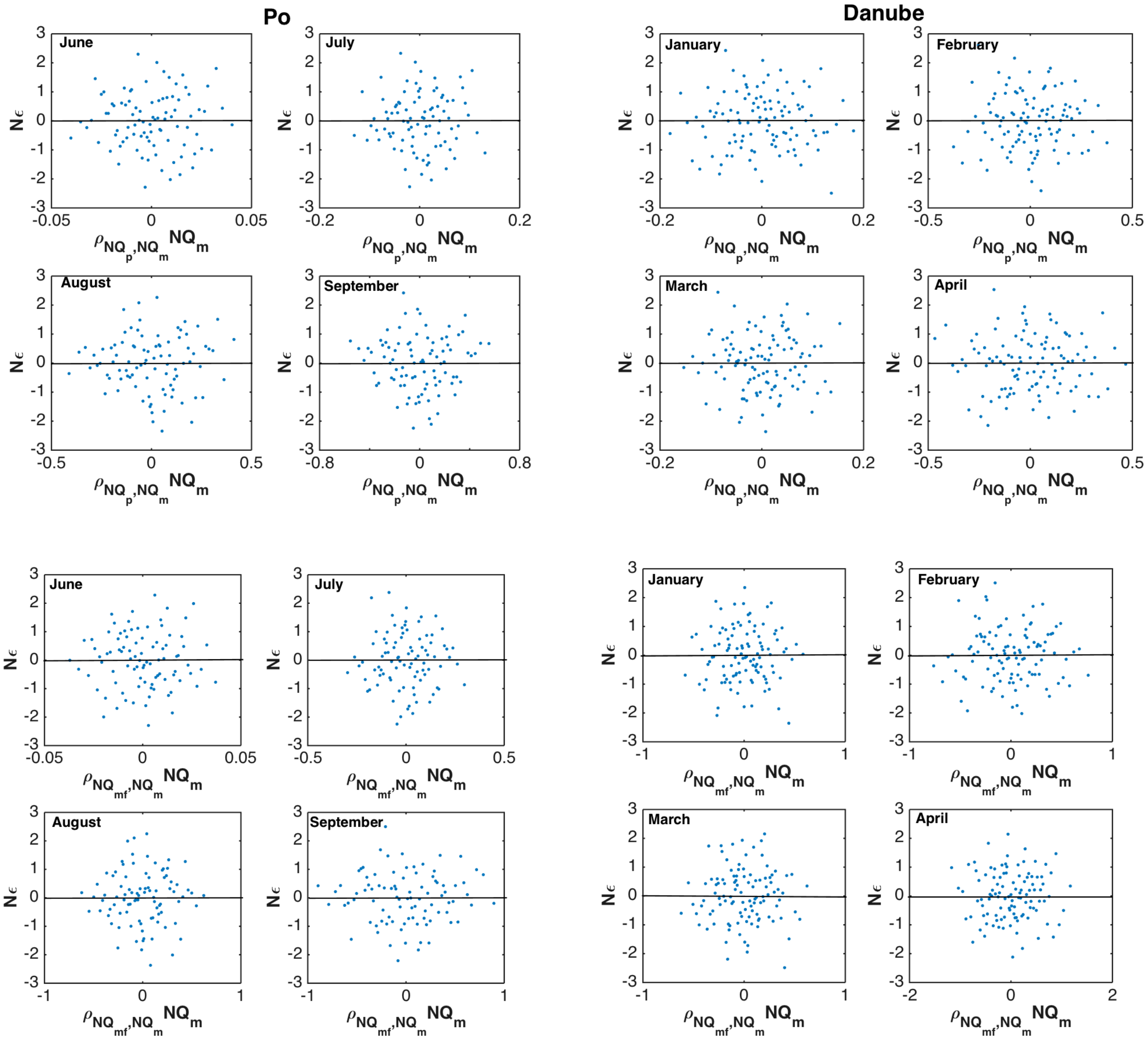

Figure 4. Residual plot of the linear regression of NQ_m on NQ_p and NQ_{mf} in the Po river (left) and upper Danube (right)

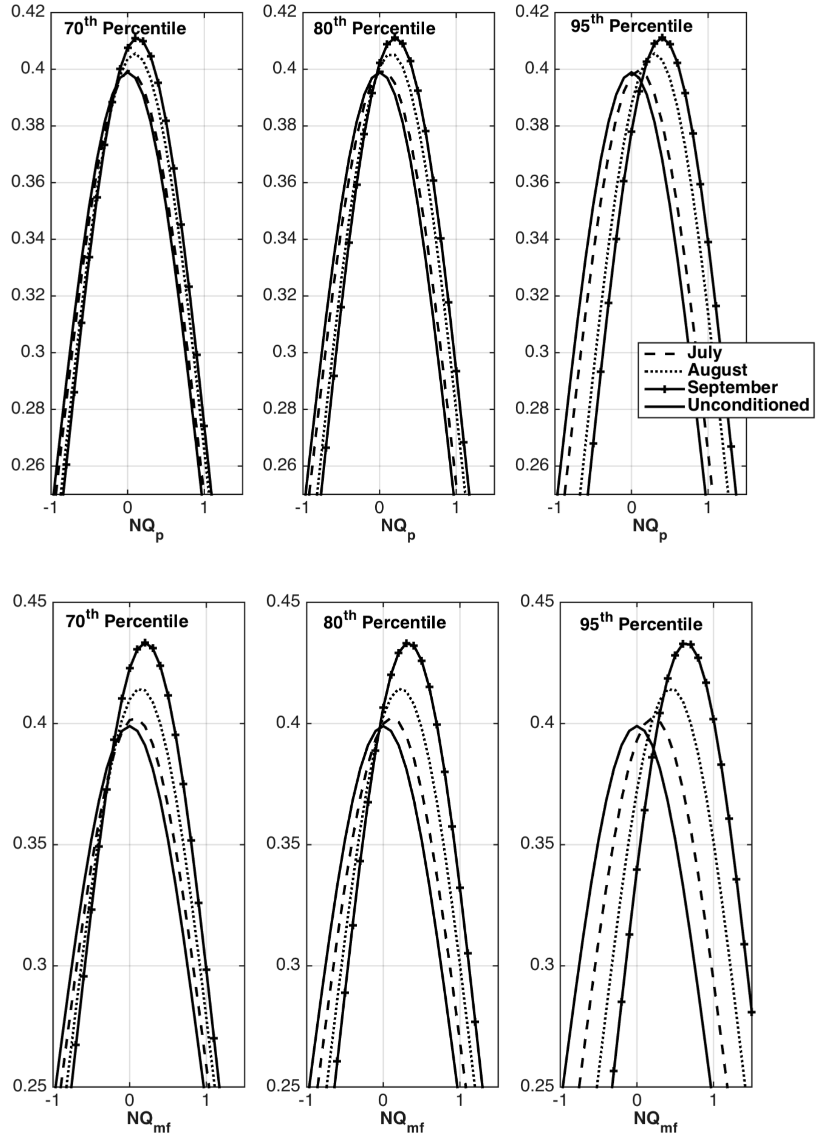

Figure 5. Probability distribution functions of the normalized dependent variables (NQ_p and NQ_{mf}) conditioned to the occurrence of the 70th, 80th and 95th percentiles of the normalized variables in the pre-flood season in the Po river.

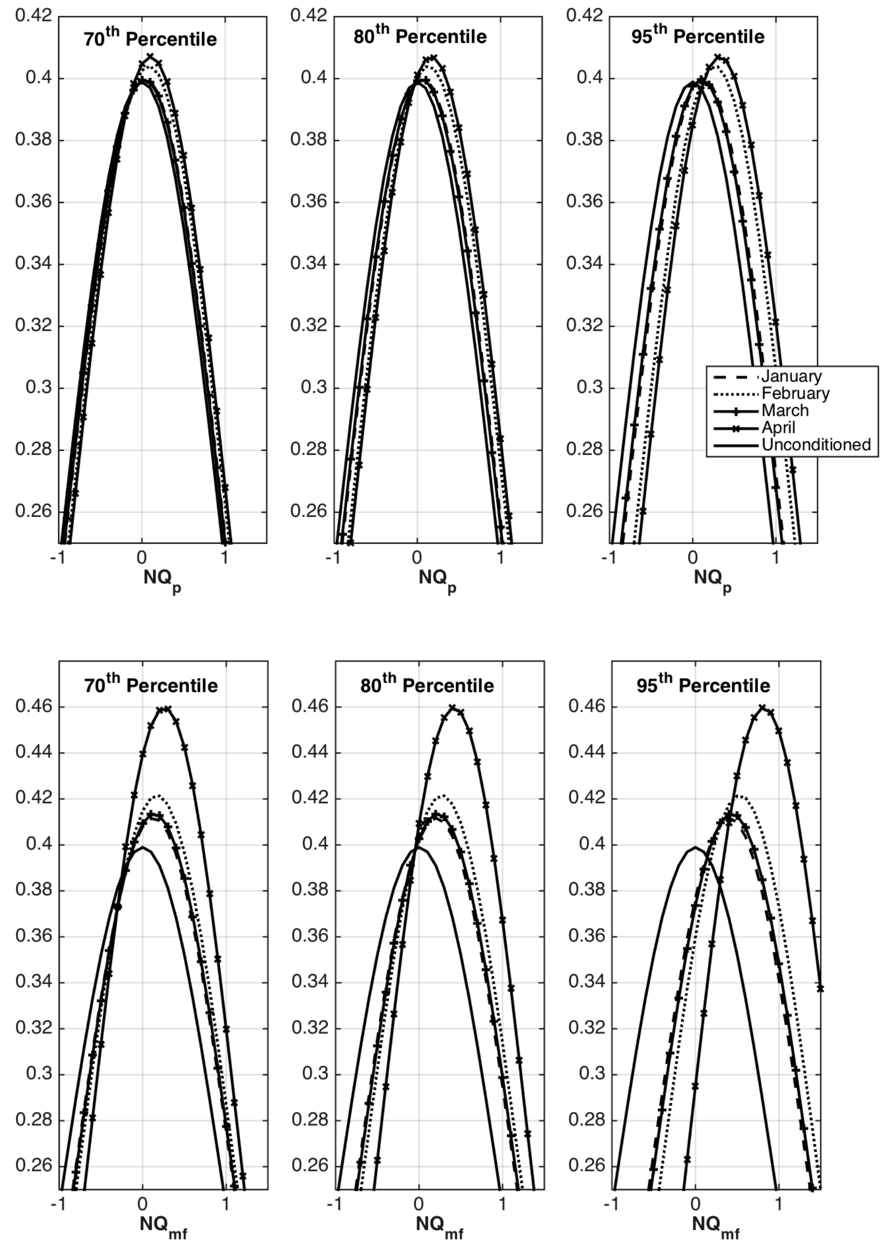

Figure 6. Probability distribution functions of the normalized dependent variables (NQ_p and NQ_{mf}) conditioned to the occurrence of the 70th, 80th and 95th percentiles of the normalized variables in the pre-flood season in the upper Danube.

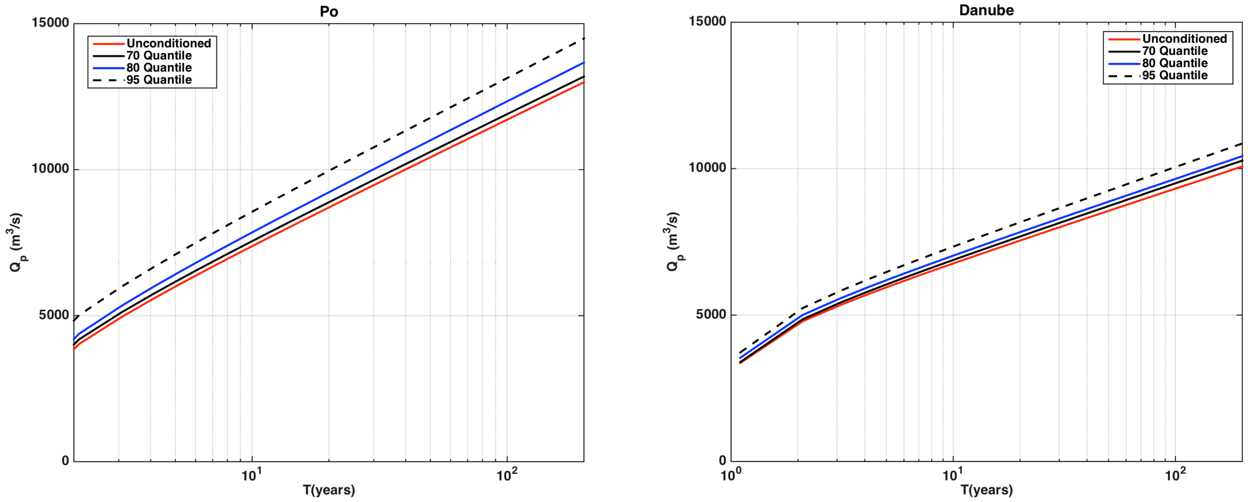

Figure 7. Peak flows in the flood season (Oct-Nov in the Po, May-July in the upper Danube) *vs* return period modeled through the EV1 distribution function. Quantiles refer to mean flows higher than usual in the previous month

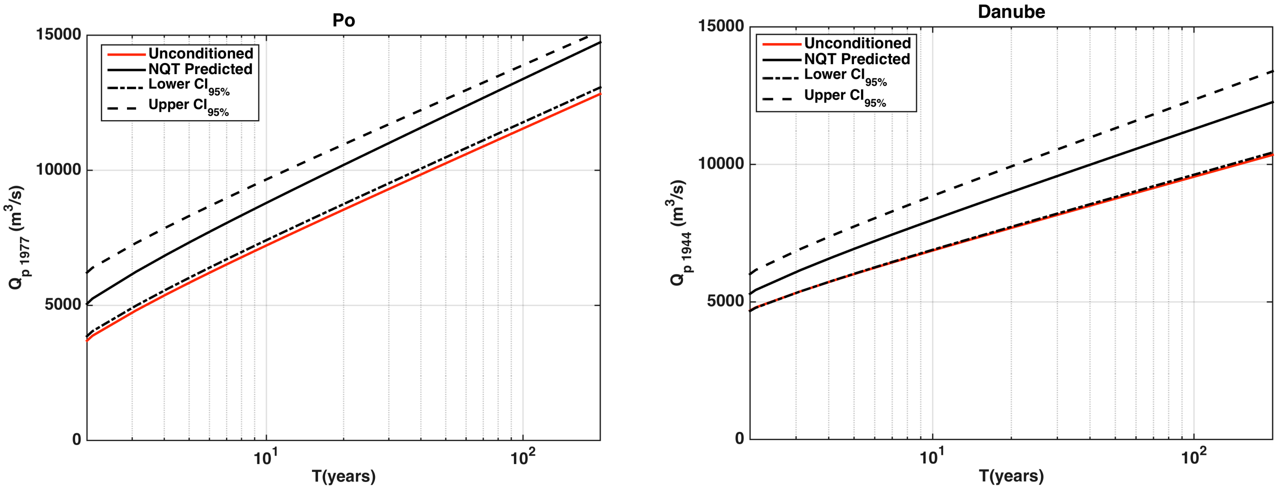

Figure 8. Leave-one-out cross validation. Unconditioned EV1 probability distribution of peak flows for the year with the wettest pre-flood season (1977 in the Po, 1944 in the upper Danube) along with conditioned distributions with related 95% confidence bands.

Table 1. Data description of observed time series. Descriptive statistics are given for non-deseasonalized data.

	Po	Danube
Observation period	1920-2009	1901-2007
Daily discharge		
Gauge location	Pontelagoscuro	Bratislava
Catchment area (km^2)	71 000	131 331
Mean (m^3 s^{-1})	1470	2053
Standard deviation (m^3 s^{-1})	1007	973
Fluvial regime	Pluvial regime. Two peak periods	Alpine regime. One peak in the summer
Monthly precipitation		
Number of weather stations	18	16
Mean (mm/month)	72	73
Standard deviation (mm/month)	17	37
Monthly temperature		
Number of weather stations	12	11
Mean (°C)	12.9	7.9
Standard deviation (°C)	7.5	7.2

Table 2. Estimated H values on deseasonalized data series applying R/S statistic (R/S), Aggregated Variance Method (AV), and Differenced Variance Method (DV)

	R/S	AV	DV
Po (Pontelagoscuro)			
Daily Q	0.81	0.74	0.94
Monthly Q	0.76	0.62	0.80
Monthly P	0.61	0.59	0.60
Monthly T	0.64	0.80	0.90
Danube (Bratislava)			
Daily Q	0.80	0.71	0.86
Monthly Q	0.75	0.54	0.79
Monthly P	0.56	0.36	0.56
Monthly T	0.61	0.76	0.70

Table 3. Pearson's cross-correlation coefficient and its 95% confidence interval between both, NQ_p and NQ_{mf} , and NQ_m for varying antecedent monthly flow. Flood season in Po: October-November. Flood season in Danube: May-July

Po			Danube		
Month	$\rho(NQ_m, NQ_p)$	$\rho(NQ_m, NQ_{mf})$	Month	$\rho(NQ_m, NQ_p)$	$\rho(NQ_m, NQ_{mf})$
September	0.24 (0.04, 0.43)	0.39 (0.20, 0.55)	April	0.20 (0.01, 0.38)	0.50 (0.34, 0.63)
August	0.18 (0, 0.37)	0.27 (0.07, 0.45)	March	0.06 (0, 0.25)	0.26 (0.07, 0.43)
July	0.06 (0, 0.26)	0.13 (0, 0.33)	February	0.16 (0, 0.34)	0.32 (0.14, 0.48)
June	0.02 (0, 0.23)	-0.02 (-0.23, 0)	January	0.07 (0, 0.26)	0.25 (0.06, 0.42)
May	-0.06 (-0.26, 0)	-0.05 (-0.25, 0)	December	-0.002 (-0.19, 0)	0.17 (0, 0.35)
April	-0.13 (-0.33, 0)	-0.07 (-0.27, 0)	November	0.05 (0, 0.24)	0.09 (0, 0.27)
March	-0.18 (-0.37, 0)	-0.12 (-0.32, 0)	October	0.13 (0, 0.31)	0.10 (0, 0.28)
February	-0.04 (-0.25, 0)	-0.05 (-0.25, 0)	September	-0.07 (-0.26, 0)	-0.08(-0.27, 0)
January	-0.07 (-0.27, 0)	-0.07 (-0.27, 0)	August	-0.21 (-0.38, -0.02)	0.09 (0, 0.27)