

* References to lines and pages, coloured in blue in the following, refer to the revised version of the manuscript.

** Tracked changes version of the manuscript is attached at the end of this document.

Reply to Referee Daniele Ganora

MAJOR COMMENTS

Reviewer:

1. The Kriging procedure (i.e. the estimation of the weights λ) is applied, for each ungauged basin, to a number on neighbouring stations which is set equal to 6, as indicated on page 13067, after a preliminary analysis. Although this approach can improve the final outcomes, I think it is in contrast with what is claimed on page 13057 (from line 10), i.e. that the geostatistical approach allows to avoid the identification of homogeneous regions. Of course, strictly speaking, Kriging does not require the homogeneity of the region; however, this pre-selection introduces a subjective element and undermines the robustness of the original method. The point is that Kriging (as well as top-Kriging) automatically provides weights on the basis of the distance of the ungauged site to the donor stations (and according to the correlation structure). Thus, the weights are (automatically) greater for close donors and smaller for donor sites far away. Moreover, weights depend on the location of the ungauged site, so the weighting structure adapts for different ungauged basins.

Under this perspective, I would like to see first an application where the whole dataset is considered. The variograms should also be reported.

Response:

The referee is right. The introduction of a fixed number of neighbouring stations considered in order to solve the kriging system could be a strong limitation, however, if at one hand this seems to introduce the hypotheses of an implicit delineation of homogeneous region on the other it is a common practice in several geostatistical applications, as well as in Top-kriging, the use of the so-called “moving neighbourhoods”. Moving neighbourhood avoid including in the interpolation very dissimilar sites, which would be associated with smaller weights, but nonetheless could be detrimental for the accuracy of the prediction. Moreover the spatial variability in the kriging methods relies on empirical variograms and a the selected theoretical variogram models, which best fit the experimental points. This computational step involves all stations in the region, so the estimates computed using a limited amount of stations somehow benefit from all the information provided by the dataset.

Action:

In the revised version of the manuscript we will include how the results vary by using moving neighbourhoods with different sizes. Examples of empirical and theoretical variograms will also be reported.

New results are reported in Sec. 5.5.2 and Fig. 10. Variograms in Fig. 4 (see also lines 11-13 page 15).

Reviewer:

2. The hypothesis that top-Kriging weights λ can be used to weight empirical FDCs is the core assumption of the method; it is a strong assumption, so I would try to verify it. I suggest one possible way to perform this task, but the authors are free to propose any other reliable method: i) consider one station among the whole dataset of N stations; ii) for that station compute the $N - 1$ weights λ ; iii) compute the $N - 1$ δ values between the empirical FDC of the selected station and the empirical FDCs of the remaining stations; iv) compare the λ values and δ values: large δ (dissimilar curves) should correspond to small λ (small weight) and viceversa; v) repeat points i)-iv) for each station.

Response:

The Referee points out a very important aspect and we thankfully acknowledge his suggestions.

Action:

In order to test and validate the basic assumption introduced with this study, in the revised version of the paper we will include a figure resulting from the analysis of the spatial consistency of the weighting scheme. The figure consists in a scatter diagram relating the distance δ values computed between curves i and j with the corresponding $\lambda_{i,j}$ value obtained in cross-validation, this for all $i,j=1,\dots,n_s$ where n_s is the number of stations belonging to the region.

[Tested and validated hypotheses are reported in Sec. 5.5.1 and Fig. 11.](#)

MINOR COMMENTS

Reviewer:

1. Due to the assumption reported in the previous comment the authors should specify, starting from the title, that the prediction of FDCs is somewhat an indirect product of the geostatistical framework. To do so, I suggest to change the title to “Geostatistical weighting scheme for prediction of flow-duration curve”.

Response:

We thank the referee for his suggestion. We agree with him that the core of the study is the introduction of an innovative linear weighting scheme which enables one to predict flow-duration curves, however we also believe that the title proposed by the Reviewer is too unbalanced towards the linear weighting scheme, which is just a mathematical expedient to perform the prediction. Also, the prediction of the FDC that we perform is indeed geostatistical within an index-flow framework. We could modify the title as: “Geostatistical prediction of flow-duration curves in an index-flow framework”, if the Handling Editor recommends it.

[See the new title reported.](#)

Reviewer:

2. The point (i) at the top of page 13058, as well as other sentences in the manuscript,

describes the TND as a characteristic of the whole curve. Actually, the flood-part of the curve (normalized discharge greater than 1) is not represented by the TND, so I would relax the statements regarding the whole curve by specifying that flood flows are not really accounted for by the TND.

Response:

Point taken, we agree with the Reviewer.

Action:

The revised manuscript will explicitly acknowledge that TDN does not describe the portion of the curve associated with low durations (high flows), also remarking that the model performances and the accuracy of the predicted FDCs are assessed on the whole curve (high flows included).

[See lines 19-20 page 9 and lines 19-23 page 15](#)

Reviewer:

3. Page 13060 line 10: the “non-decreasing” property of FDCs actually depends on the way the curve is represented. If ordered discharges are plotted against the non-exceedance probability, the curve is non-decreasing; otherwise (as in this paper), if the exceedance probability is used, the curve is non-increasing. I suggest to use “monotone relationship” to account for both the possible representations.

Response:

We agree with the referee.

Action:

We will adopt “monotone (i.e. non-increasing in this paper) relationship” in the revised manuscript.

[See line 9 and 19 page 8, lines 19-20 page 25.](#)

Reviewer:

4. In page 13064, from line 14, the authors introduce an operational problem due to the different length of the period-of-record FDCs. The issue regards the lowest value dimensionless duration d which vary for different record lengths and thus affects the computation of the TND. The proposed solution is to fix a maximum d , which is equivalent to cut the right tail of the FDC at the specified d , in order to have the same limit for TND calculation for each FDC. I think this operation would be no longer necessary if the curves were previously resampled at a set of pre-imposed durations. A possible resampling set is $d_i = 1:i/(N + 1)$ with $N = 365$ ($i = 1...365$) if one refers to the equivalent number of days in a year, but it is not the only possible resampling. In fact, a resampling procedure has already been implemented by the authors in section 5, over 20 points equally spaced in the z space. Since this resampling procedure is essential to predict the FDC, it should be applied before the TND computation to keep the framework consistent.

Response:

The Referee raises a good point. and we thank him for the possibility to clarify it. We believe that resampling, as the referee proposes, could be a viable solution if the numerical computation of the TND values were computationally demanding, which is not the case. Therefore we still believe that interpolation should be avoided, when possible. We did use interpolation (20 points, which are enough to characterize a curve according to e.g. Ouarda et al., 2012), but only for assessing the prediction accuracy and compare the performance of different models at different gauges.

Action:

The revised manuscript will make it clear that the 20-point resampling is used only for assessing the prediction accuracy and comparing the performances of different models, while empirical TND values are computing using all the information available.

[See lines 19-20 page 15, lines 9-10 page 9.](#)

TECHNICAL NOTES AND MISSPELLINGS

Reviewer:

1. Page 13057: the text block of lines 13-16 has basically the same information as the lines 21-25. Please reformulate the paragraph to remove redundant information.
2. Parentheses around citations of equation numbers are often missing throughout the text (se for example P13059 L 14; P13060 L 17; P13064 L16; etc.) and should be added.
3. In plots showing FDCs in the frequency domain I would use “Exceedance frequenc” or “Dimensionless duration” rather than “Duration” which, instead, recall a dimensional time variable. The same correction should be done throughout the text, for instance before eq. (4) and on page 13064.
4. Missing punctuation after eq. (7).

Response:

1. We will remove “without the delineation of homogeneous regions” from the statement.
2. Ok. We will rectify.
3. The Reviewer is right, we will clarify in the text that with d we refer to a dimensionless duration equal to the exceedance probability, and then we will use “Duration d [-]” in all Figure (included the central panel of Figure 2).
4. Ok. We will rectify.

[Corrected as suggested.](#)

Reply to Anonymous Referee #2

We thankfully acknowledge Referee#2's comments, which we find extremely useful for improving the presentation of the work, enhancing its accuracy and rigorousness. We report below our replies (the actual reply is denoted by "Response", while "Action" briefly details the revisions to the manuscript) to all referee's comments (indicated by "Reviewer").

GENERAL COMMENTS

Reviewer:

The paper presents a novel method for prediction of flow-duration curves in ungauged basins, which is of interest to the readers of HESS and which would make a valuable contribution to the literature. However, before publication the quality of the paper should be improved by addressing a number of methodological and technical issues, including a better discussion of the limitations and assumptions in the method as well as the language and structure of the paper. Many of the issues were brought up by the first reviewer and since these are already mentioned I will focus this review on other aspects of the paper.

The data from several of the gauging stations are not independent since they are coming from stations that are located upstream/downstream on the same river. This would likely make it easier to predict streamflow at a new location when part of the catchment is in fact gauged and these data are used in the prediction (especially when the method is based on spatial proximity), and this might therefore limit the predictive power in completely ungauged catchments. How similar are the upstream/downstream FDCs? How does the fact that upstream/downstream stations are included affect the evaluation of the method? Please also discuss how this relates to the assumptions implicit in the different regionalisation methods that are used: the top-kriging as well as the regression-based methods.

Response:

The Reviewer raises a good point, which is of particular interest for Top-kriging because the procedure incorporates in the hydrological predictions the nested structure of the stream network (see e.g. Skøien et al., 2006), and probably less interesting for the previous regionalization studies that were used in our study only for benchmarking the results of TNDTK.

Action:

The additional analysis suggested by Referee D. Ganora (relationship between λ and δ values) will be performed by considering all catchment pairs in the study area, and also by referring at nested or unnested catchment pairs separately. This first analysis will shed some light on the relationship between the stream-network structure and

similarity/dissimilarity between empirical FDCs. Also, a new analysis will be performed. TNDTK will be applied in cross-validation by neglecting all information collected for the site of interest, but also upstream or downstream the site of interest, and the performance of the procedure will be compared with the performances obtained through the leave one out cross validation (LOO). A discussion of the results of these two additional analysis and additional diagram will be included in the revised manuscript.

[New analysis added, see Sec. 5.5.3 and Figs. 11 and 12.](#)

SPECIFIC COMMENTS

Reviewer:

Abstract. There is a lot of information about the method in the abstract but very little information about the results (only one sentence), more information about the findings of the study should be given.

Response:

We thank the referee for the suggestion.

Action:

We will add some more lines about the results in the revised abstract.

[See lines 22-26 page 2.](#)

Reviewer:

Page 13058, line 4. The aim, part (iii) could be better formulated to rather be about “to evaluate” the method in comparison to other regionalisation methods instead of “to use”.

Response:

We agree with the Referee.

Action:

We will replace “use” with “evaluate”.

[We preferred to use the verb “to assess” instead of “to evaluate”. See line 7 page 6 if it could be reasonable.](#)

Reviewer:

Since data from some of the basins in the study region are used in Fig 1 it would make more sense to describe the study region and data as the second section after the introduction, otherwise it is not clear what the basin numbers in Fig 1 refer to.

Response:

We understand Reviewer point, but we prefer to have a classical structure for our manuscript, i.e. theoretical concepts presented before the study area and practical application.

Action:

We will include a reference to Section 4 – Study Area in the manuscript body when Fig. 1

is recalled, and we will also refer to Section 4 in Fig. 1 caption.

Corrected as suggested.

Reviewer:

Page 13066, line 14. “Rather dense raingauge network” specify this in terms of numbers of gauges per km².

RESPONSE:

Agreed.

Action:

The revised manuscript will report an indication of the raingauge network density (i.e. 1 raingauge per ≈ 50 km²).

See lines 8-9 page 14.

Reviewer:

Page 13068, Line 6-9. The cross-validation is described as “comprehensive”, but ideally (if there are more catchments than in this case) one would set aside a whole set of catchments in a separate validation set, which would then constitute a stronger test than a cross-validation. Also, what does “As anticipated” refer to here?

Response:

Split-sample validation is a powerful validation procedure, which is routinely used in some hydrological studies, but it is seldom adopted for testing regional models. LOOCV is a standard validation approach for evaluating the accuracy of regional models as, once the model structure is set, it simulates the ungauged conditions at each and every site in the study region (this is why we used the term “comprehensive”). Therefore it provides very valuable information on how the proposed model is supposed to perform when applied to ungauged sites in the study area. There is a vast hydrological literature on statistical regionalization in which LOOCV is used (these are only a few recent examples: Kroll and Song, 2013; Laaha et al., 2013; Salinas et al., 2013; Srinivas et al. 2008; Wan Jaafar et al., 2011)

Action:

The sentence will be reformulated as follows: “As mentioned in Section 1, a leave-one-out cross-validation ...” will replace “As anticipated, a comprehensive leave-one-out cross-validation ...”.

See line 1 page 16.

Reviewer:

Page 13068, line 10-20. It is not clear if the gauging station for the ungauged station is removed before the estimation of the variograms. If not, why is this not done? If it is included then some of the information from the ungauged basin is used in the method and

it is not truly a prediction for an ungauged basin. Please clarify this.

Response:

We run set of preliminary investigations to assess the sensitivity of empirical semivariogram to the LOOCV, and the results pointed out negligible variations.

Action:

The preliminary analyses will be explicitly mentioned in the revised manuscript.

[See lines 5-10 page 13.](#)

Reviewer:

Page 13068, line 16. The choice of $n=6$ neighbouring stations needs to be better motivated. This could be done by presenting a figure of cross-validation results plotted against the number of surrounding stations used.

Response:

We thank the referee for the suggestion and we will add that figure in the revised manuscript. We invite the referee to read the answer we give to Referee D. Ganora , were we also explain how we want to modify the manuscript.

[Sec. 5.5.2 and Fig. 10](#)

Reviewer:

Page 13068, Line 23 to Page 13069, Line 4. This information is quite general and vague, and the steps i-iv in cross-validation methods are probably obvious to most readers, so this could be excluded.

Response:

Agreed.

Action:

The steps will be omitted by dropping the text that follows “, but the rationale is the same.”

[Corrected as suggested, avoiding to write “, but the rationale is the same.”.](#)

Reviewer:

Page 13074, Line 10 “More accurate predictions for 10 out of 18 catchments”, this is still just about half of the cases and does not distinctly “confirm good performance”. Please write this in a more nuanced way.

Response and Action:

Agreed. We will take into account this advise in the revised manuscript.

[We changed “more accurate predictions” with “better accuracy”, see line 15 page 21.](#)

Reviewer:

Page 13075, Line 11-12 and Page 13078, Line 14-16. It is highlighted as an advantage that the method only relies on spatial proximity, however this may also be an important limitation of the method in other regions where e.g. geology have a larger impact on streamflow such that the hydrological behaviour of nearby catchments may be quite different. In the study, there was also poorer performance for the 3701 catchment that had a different behaviour. This limitation and the general applicability of the method in other areas should be better discussed.

Response:

Point taken.

Action:

The sentence indicated by the Reviewer in the Conclusions (p. 13078) will be integrated with a brief discussion of the sensible point raised by the Reviewer.

[See lines 22-26 and 1-2 pages 24-25.](#)

Reviewer:

The Conclusions section is too long, it is about as long as the discussion section. In its present form it is written as an extended abstract describing the whole study. It would be better to just shortly (e.g. with a few bullet points) describe the main findings/conclusions that can be drawn from the paper, the rest of the information does not need to be repeated here.

Response:

The referee is right.

Action:

We will reduce the length of the Conclusions by removing redundant lines and focusing on the study outcomes.

[Corrected as suggested.](#)

Reviewer:

Table 1. This table should show the characteristics for each basin instead of the statistics for the whole dataset to make it possible to interpret the results for the different basins. It should also give the number of years with data for each catchment.

Response:

Agreed.

Action:

The complete set of catchment attributes will be illustrated in annexed diagrams (e.g., PNG images accessible via “Supplement link”). Unfortunately, some of the data cannot be freely distributed, but their graphical representation can.

The complete set of catchment characteristics are available as “Supplement” in PDF format, rather than PNG. See file “catchment_attributes.pdf”.

TECHNICAL COMMENTS

Reviewer:

Table 1. Too many significant digits are given for MAP.

Figure 1. should be “thick line” instead of “tick line”

Figure 3. Show maps of MAP and MAF as well.

Figure 6 and Figure 8. No units are given on the axes.

Page 13058, line 8. The abbreviation MAP for Mean Annual Precipitation should be introduced here and used consistently for the remainder of the paper. The English language needs to be checked throughout the paper since the text is full of minor grammatical errors (e.g. using “then” instead of “than” in many places, “reminder” instead of “remainder” on p 13067, line 11, “routinely” should be “repeatedly” on p 13060, line 2, etc.). I also recommend avoiding the use of emphasis words such as “very”, “excellent”, “extremely”, “scrupulously”, “superior”, etc. Grammatically it would be more consistent to also write the steps 1-6 in the cross-validation on Page 13068 in the past tense instead of present. The paper could also benefit from a revision of the text to reduce repetition, e.g. Page 13074, Line 2-5 is repeated information and could be excluded.

Response and Action:

We agree with the Referee. We will take all of his suggestions (thanks!) into account while revising our manuscript.

Corrected as suggested. We preferred to keep Fig. 3 as it was (just with few graphical corrections), showing MAF and MAP data in the “Supplement” PDF file.

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Geostatistical prediction of flow-duration curves in an index-flow framework

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Abstract

~~We present in this study an adaptation~~ An empirical period-of-record Flow-Duration Curve (FDC) describes the percentage of time (duration) in which a given streamflow was equaled or exceeded over an historical period of time. FDCs have always attracted a great deal of interest in engineering applications because of their ability to provide a simple and yet comprehensive graphical view of the overall historical variability of streamflows in a river basin, from floods to low-flows. Nevertheless, in many practical applications one has to construct FDC in basins that are ungauged or where very few observations are available. We present an application strategy of Topological kriging (or Top-kriging), which makes the geostatistical procedure capable of predicting flow-duration curves (FDCs) in ungauged catchments. Previous applications of Top-kriging mainly focused on the prediction of point streamflow indices (e.g. flood quantiles, low-flow indices, etc.). In this study Top-kriging is used to predict FDCs in ungauged sites as a weighted average of standardised empirical FDCs through the traditional linear-weighting scheme of kriging methods. Our study focuses on the prediction of ~~period-of-record~~ FDCs for 18 unregulated catchments located in Central Italy, for which daily streamflow series with length from 5 to 40 ~~yr~~ years are available, together with information on climate ~~referring to for~~ the same time-span of each daily streamflow sequence. Empirical FDCs are standardised by a reference ~~streamflow~~ index-flow value (i.e. mean annual flow, or mean annual precipitation times the catchment drainage area) and the overall deviation of the curves from this reference value is then used for expressing the hydrological similarity between catchments and for deriving the geostatistical weights. We performed an extensive leave-one-out cross-validation to quantify the accuracy of the proposed technique, and to compare it to traditional regionalisation models that were recently developed for the same study region. The cross-validation points out that Top-kriging is a reliable approach for predicting FDCs ~~, which can significantly outperform traditional regional models in ungauged basins~~ with Nash & Sutcliffe Efficiency measures ranging from 0.85 to 0.96 (depending on the model settings) in cross-validation, very low biases over the entire duration range, and an enhanced representation of the low-flow regime.

1 Introduction

An empirical Flow Duration Curve (FDC) graphically represents the percentage of time (or duration) in which the streamflow can be equalled or exceeded over a historical period of time (see e.g. Vogel and Fennessey, 1994). Empirical FDCs are often used to represent the streamflow regime of a given catchment when an adequate number of streamflow observations are available. A deterministic hydrologist would probably refer to an FDC as a key signature of the hydrological behaviour of a given basin, as it results from the interplay of climate, size, morphology, and permeability of the basin; a statistical hydrologist would refer to an FDC as the exceedance probability, or equivalently the complement to the probability distribution function (cdf) of streamflows (see e.g. Castellarin et al., 2013).

Because of their ability to provide a simple and yet comprehensive graphical view of the overall historical variability of streamflows in a river basin, from floods to low-flows, and their peculiarity of being readily understandable by those who do not have a strong hydrological background, empirical FDCs are routinely used in several water-related studies and engineering applications such as hydropower generation, design of water supply systems, irrigation planning and management, wasteload allocation, sedimentation studies, habitat suitability, etc. (see e.g. Vogel and Fennessey, 1995).

The literature reports two different representations of empirical flow-duration curves, depending on the reference period of time (see Vogel and Fennessey, 1994): (i) period-of-record flow duration curves (POR-FDCs), constructed on the basis of the entire observation period and (ii) annual flow duration curves (AFDCs), constructed year-wise. The two representations are complementary to each other and should be selected by practitioners depending on the water problem at hand (Castellarin et al., 2004b). For instance, AFDCs are useful for quantifying the streamflow regime in a typical hydrological year, or in a particularly wet or dry year (see Vogel and Fennessey, 1994); POR-FDCs are a steady-state representation of the long-term streamflow regime and can be effectively used, for instance, for patching and extending streamflow data (Hughes and Smakhtin, 1996) or for assessing the long-term hydropower potential of a given site.

In many practical applications one has to predict FDCs at ungauged catchments or catchments for which the available hydrometric information is sparse (see e.g. Castellarin et al., 2013). This task is often addressed by developing regional models of FDCs. The scientific literature proposes several of such models that adopt different approaches to the problem: some model regard the curves as the exceedance probability function of streamflows and regionalise the parameters of theoretical frequency ~~distributions~~ distributions (see Fennessey and Vogel, 1990; LeBoutillier and Waylen, 1993; Castellarin et al., 2007; Mendicino and Senatore, 2013); similarly, some other adopt a suitable mathematical expression for representing the curves and regionalise the expression parameters (Franchini and Suppo, 1996; Mendicino and Senatore, 2013); finally, some other do not make any attempt to mathematically represent the curves, they rather standardise empirical curves constructed for gauged catchments that are hydrologically similar to the target site (i.e. catchments that are characterised by a similar physiographic, pedologic and climatic conditions, also referred to as donor sites, see e.g. Kjeldsen et al., 2000) by an index streamflow (e.g. mean annual flow), and then average the dimensionless curves to predict the standardised FDC for the study catchment. The averaging procedure may (see e.g. Ganora et al., 2009), or may not (see e.g. Smakhtin et al., 1997), adopt a weighting scheme, which gives more importance to donor sites that are more hydrologically similar to the target site. The literature commonly groups these regionalisation procedures into parametric (i.e. procedures that parameterise FDCs and then regionalise parameters, like the first two examples) and non-parametric ~~procedures~~ (i.e. procedure that dispense with a parameterisation of the curves, like the third example, see e.g. Castellarin et al., 2004a, 2013) procedures.

It is a common argument that an accurate representation of FDCs for daily streamflows requires probabilistic models (or mathematical expressions) with four or more parameters (LeBoutillier and Waylen, 1993; Castellarin et al., 2007), which control the position, scale and shape of the distribution. This hampers the construction of reliable regional models, due to the large uncertainty that is commonly associated with regional relationships that express the shape parameters in terms of physiographic and climatic catchment descriptors (see Castellarin et al., 2007). As a result, ~~classical approaches~~ Ganora et al. (2009) recently revisited the classical approach to FDCs regionalisation based on averaging standardised curves constructed for neighbouring

gauged sites (Smakhtin et al., 1997) ~~have been recently revisited through~~, they proposed a mathematical model that enables the user to quantify the dissimilarity between empirical FDCs and associate this dissimilarity with a distance in the multidimensional space of catchment descriptors (Ganora et al., 2009). An innovative feature of this approach is the possibility to weight each empirical FDC according to the distance between each gauged basin and the target site in the space of catchment descriptors, therefore accounting for the hydrological similarity of the donor sites with the site of interest. Like many of the traditional approaches proposed in the literature, though, the approach proposed in Ganora et al. (2009) (1) requires a preliminary subdivision of the study area into homogeneous pooling-groups of sites (i.e. clustering), (2) predicts a standardised (i.e. dimensionless) FDC for the target site, which needs then to be multiplied by a dimensional scale index (e.g. an indirect estimate of mean annual streamflow) in order to be of practical use. Both steps are critical phases of a regionalisation process. In particular concerning step (1), geostatistical regionalisation approaches have been shown to be particularly effective in dispensing with the preliminary identification of homogeneous pooling-group of sites while using regional hydrological information for predicting streamflow indices in ungauged catchments (e.g. flood quantiles, low-flow-indices, etc.: see e.g. Chokmani and Ouarda, 2004; Skøien et al., 2006; Castiglioni et al., 2009, 2011; Archfield et al., 2013; Laaha et al., 2013); yet no geostatistical procedure has been developed that specifically addresses the problem of FDC regionalisation, aside from an interpolation of the curves in the physiographic-space through a three-dimensional kriging, which is not a geostatistical procedure in the strict sense (see Castellarin, 2014).

Our paper focuses on the derivation of a geostatistical technique that addresses both limitations mentioned above for the prediction of FDCs in ungauged sites. We adopt Topological kriging or Top-kriging, which is a block-kriging with variable support area that interpolates streamflow-indices along stream networks (see e.g. Skøien et al., 2006). Top-kriging has been proved to be particularly successful in predicting point streamflow values (e.g. low-flow and flood quantiles, mean annual flood, stream temperatures, etc.) in various geographical and climatic contexts ~~without a delineation of homogeneous regions~~ (see e.g. Merz et al., 2008; Castiglioni et al., 2011; Vormoor et al., 2011; Archfield et al., 2013; Laaha et al., 2013).

We adopt Top-kriging as the core tool for predicting standardised (i.e. divided by mean annual flow) and dimensional long-term daily FDCs on the basis of empirical period-of-record curves (POR-FDCs, hereafter referred to as FDCs for the sake of brevity) constructed for neighbouring streamgauges.

The idea behind our study is (i) to identify a meaningful empirical point value (or index) that fully characterises the whole empirical FDC, (ii) to model the spatial correlation structure, or the spatial variability, of this ~~point~~ index over the study region through Top-kriging and (iii) to ~~use~~ assess the capability of this very spatial correlation model to predict FDCs in ungauged sites by weighting neighbouring empirical FDCs. We present two possible applications of the proposed procedure, the first one predicts standardised FDCs, that is FDCs divided by Mean Annual Flow (MAF), the second one predicts FDCs divided by the product between Mean Annual Precipitation (MAP) and drainage area. MAP is generally easier to predict than MAF in ungauged sites, due to the higher density of raingauging networks relative to streamgauging ones. The second application can therefore be used to ~~obtain a prediction of the dimensional FDCs for the target size~~ predict dimensional FDCs in ungauged sites.

The approach is developed and tested through a comprehensive leave-one-out cross-validation procedure for a rather wide geographical region located in Eastern-Central Italy including 18 unregulated river basins. Castellarin et al. (2007) propose regional models of long-term daily FDCs for this area, which we use in this study as benchmark models for comparing the accuracy and reliability of the proposed approach.

2 Geostatistical hydrological prediction in ungauged sites

2.1 Top-kriging

Top-kriging is a powerful geostatistical procedure proposed by Skøien et al. (2006) which performs hydrological predictions at ungauged sites along stream-networks on the basis of the empirical information collected at neighbouring gauging stations. As kriging techniques, the spatial interpolation is obtained in Top-kriging by a linear combination of the empirical val-

ues; therefore, the unknown value of the streamflow index of interest at prediction location x_0 , $\hat{Z}(x_0)$, can be estimated as a weighted average of the variable measured in the neighborhood:

$$\hat{Z}(x_0) = \sum_{i=1}^n \lambda_i Z(x_i) \quad (1)$$

where λ_i is the kriging weight for the empirical value $Z(x_i)$ at location x_i , and n is the number of neighbouring stations used for interpolation. Kriging weights λ_i can be found by solving the typical ordinary kriging linear system [2\(2\)](#), with the constrain of unbiased estimation [2b\(2b\)](#):

$$\sum_{j=1}^n \gamma_{i,j} \lambda_j + \theta = \gamma_{0,i} \quad i = 1, \dots, n \quad (2a)$$

$$\sum_{j=1}^n \lambda_j = 1 \quad (2b)$$

where θ is the Lagrange parameter and $\gamma_{i,j}$ is the semi-variance between catchment i and j . The semi-variance is also referred to as variogram in geostatistics and represents the space variability of the regionalised variable Z . A peculiar feature of Top-kriging is to consider the variable defined over a non-zero support S (i.e. the catchment drainage area)(Cressie, 1993; Skøien et al., 2006); this implies that the kriging system [2\(2\)](#) remains the same, but the gamma values between the measurements need to be obtained by regularization, that is the smoothing effect of support area S on the point variogram, which is computed by applying an integral average of the variable Z over S . After this, the point variogram can be back-calculated by fitting aggregated variogram values to the sample variogram (details can be found in Skøien et al., 2006).

2.2 Total negative deviation (TND)

Top-kriging could in principle be directly applied to interpolate single streamflow values associated with a given duration (i.e. streamflow quantiles). Therefore, similarly to what proposed in Shu and Ouarda (2012), a regional prediction of FDCs could be obtained by **routinely**

repeatedly applying Top-kriging r times, where r is the number of durations considered to provide an accurate representation of the curve (e.g. 15–20, see Shu and Ouarda, 2012), and then by interpolating the r predicted streamflow quantiles to obtain an FDC. Nevertheless, each FDC is a continuum resulting from the complex interplay between climate conditions and geomorphologic catchment characteristics (see e.g. Yaeger et al., 2012; Yokoo and Sivapalan, 2011; Beckers and Alila, 2004). This continuum would be lost, entirely or in part, by using the approach outlined above; moreover, this prediction strategy might not preserve a fundamental property of FDCs, that is the ~~non-decreasing monotone~~ (i.e. non-increasing in this paper) relationship between streamflow and duration.

Our main goal is to develop a Top-kriging procedure that regionalises the whole curve seen as a single object. In geostatistical applications one should define a “regionalised variable” to produce a ~~characterization~~ characterisation of the spatial variability of the investigated phenomenon. As mentioned above, Top-kriging has been shown to be particularly reliable in predicting point (i.e. single values) streamflow indices in ungauged locations. Therefore a viable strategy could be to identify a point index that effectively summarises the entire curve, and to compute the Top-kriging λ_i values of (~~Eq-2~~ Eq. (2)) relative to this index. These values could then be used for averaging neighbouring empirical FDCs and predicting the FDC at the (ungauged) site of interest. This prediction strategy would regard each curve as a single object, and the linear interpolation of the curves (see also Sec. 3) would preserve the ~~non-decreasing monotone~~ relationship between streamflow and duration.

Some studies in the literature suggest to use the FDC slope as an overall index for the curve (see e.g. Sawicz et al., 2011). We believe though that the definition of such an index is associated with some degrees of subjectivity (e.g. which lower and upper durations to consider for the computation of the slope), and may be hard to define in some cases (e.g. ephemeral and intermittent streams).

Focusing on FDCs, Ganora et al. (2009) quantify the hydrological dissimilarity between a pair of catchments as the area between the corresponding empirical standardised (i.e. divided by mean annual flow) FDCs: two hydrologically similar catchments will show similar standardised curves, hence a small area between the curves, whereby two basins that are **with**

completely different in terms of hydrological behaviour will be characterised by highly different FDCs, and therefore the area between the curves will be [high](#)[large](#). Following this background idea, we propose to summarise the [entire](#)-FDC through a point index which we term Total Negative Deviation (TND) between a dimensionless (i.e. standardised by a reference streamflow value) FDC and [one](#)[1](#),

$$\text{TND} = \sum_{i=1}^m |q_i - 1| \Delta_i \quad (3)$$

where q_i represents the [i](#)[th](#)[-th](#) empirical dimensionless streamflow value, Δ_i is half of the frequency interval between the [i + 1](#)[th](#) [and i - 1](#)[th](#) ([i + 1](#)[\)-th](#) and ([i - 1](#)[\)-th](#) streamflow values, and the summation includes only $i = 1, \dots, m$ dimensionless streamflow values that are lower than 1 (i.e. negative deviation). [m](#) [stands for the length of the dimensionless streamflow sample once values larger than 1 are excluded](#).

Empirical TND values are proportional to the filled areas in Fig. 1, where black thick curves represent the empirical FDCs. More specifically, Fig. 1 represents the dimensionless empirical FDCs that were constructed for three streamgauges ([see Sec. 4 for a brief description of the study area](#)) by using two standardisation methods: in one case the curve is standardised by the mean annual flow (standardisation by MAF, TND₁, top panels of Fig. 1); in the other case the curve is standardised by MAP*, that is a reference streamflow equal to the catchment area A times the mean annual precipitation [MAP](#) (standardisation by MAP*, TND₂, bottom panels in Fig. 1) (see details on standardisation procedure in [See](#)[Sec. 3.2](#)).

[Even though](#) TND defined by Eq. (3) and illustrated in Fig. 1 [does not describe the portion of the curve associated with low durations \(high flows\)](#), it is very informative on the shape of the FDC, which, in turn, is controlled by climatic, physiographic and geo-pedological characteristics of the catchment. [Distinctions between the dominant hydrological functions in different seasons within the same catchment can be highlighted by TND](#). Catchments that are dominated by rapidly responding near-surface runoff processes have steeper FDC slopes, and therefore larger TND, while FDCs are less steep where slower responding runoff generation processes prevail, and under these circumstances TND will be smaller. This is related to functional simi-

larity: catchments that store and retain more water should have smaller ~~TND~~TNDs. The magnitude of TND is related not only to the climate but also to how efficiently the catchment partitions water into runoff.

3 Top-kriging of flow-duration curves

3.1 Construction of empirical FDCs

The construction of empirical FDCs for gauged sites is straightforward: (i) pooling all observed streamflows in one sample, (ii) ranking the observed streamflows in ascending order and (iii) plotting each ordered observation vs. its corresponding duration, ~~which is usually dimensionless. The~~. We adopt as duration of the i ~~th~~-th observation in the ordered sample ~~is equal to an~~ in our study the estimate of the exceedance probability of the observation, $1 - F_i$. If F_i is estimated using a Weibull plotting position, the duration d_i is,

$$d_i = \text{Prob}\{Q > q_i\} = 1 - \frac{i}{N+1} \quad (4)$$

where N is the length of daily streamflows observed in a gauged site and $i = 1, \dots, N$ is the i ~~th~~-th position in the rearranged sample.

A common representation of FDCs reports log-flows on the ~~y-axis~~y-axis and the duration on the ~~x-axis~~x-axis (see Fig. 1). Another common representation adopts a log-normal space instead, in which log-transformation of streamflows are still reported on the ~~y-axis~~y-axis, while the ~~x-axis~~x-axis reports duration expressed as a normal standard variate z ,

$$z_i = \Phi^{-1}(1 - d_i) \quad (5)$$

where Φ is the cdf of the standard normal distribution. The combination of the two transformations improves significantly the readability of the FDC (see Fig. 2), the log-transformation enhances the representation of observed streamflows, which usually spans over two or more orders of magnitude, while expressing the duration as a standard normal variate improves the visualization of small and large durations, that is flood- and low-flows, respectively.

3.2 Computation of empirical TND values

According to what [we](#) anticipated in Sec. 2.2, two different standardisation procedures are considered for computing TND values:

TND₁

TND values are computed after standardisation by Mean Annual Flow (MAF), that is the traditional way to standardise FDCs.

TND₂

TND values are computed for FDCs that are standardised by a rescaled Mean Annual Precipitation (MAP*). The standardisation is performed by dividing each streamflow value by the empirical catchment-scale MAP value, rescaled to basin size as,

$$\text{MAP}^* = \text{MAP} \cdot A \cdot \text{CF} \quad (6)$$

where A is the catchment area and CF is a unit-conversion factor (e.g. if streamflows are in $\text{m}^3 \text{s}^{-1}$, MAP in ~~mm~~-mm [per](#) year and A in km^2 , then ~~CF = 3.171 × 10⁻⁵~~ [CF = 3.171 × 10⁻⁵ \[-\]](#)). Once the dimensionless FDC is predicted for an ungauged site, then a dimensional FDC can be obtained by multiplying the curve by a local catchment-scale estimate of MAP*.

The idea behind the choice of two different standardisations of FDCs derives from two different purposes: (TND₁) MAF standardisation is the traditional choice when an index-flow regionalisation approach, with MAF being the index-flow), is used to regionalise FDCs (see Castellarin et al., 2004b; Ganora et al., 2009). Such an approach, as already mentioned, needs then an appropriate regional model for predicting the index-flow in ungauged basins (e.g. a multiregression model) in fact, once a standardised FDC is predicted for an ungauged site, then a dimensional FDC can be obtained by multiplying the dimensionless curve by an estimate of MAF for the site of interest, ~~which~~. [Setting up a regional model for predicting MAF](#) is a critical and delicate step in the regionalisation procedure (see e.g. Brath et al., 2001; Castellarin et al.,

2004a); (TND₂) MAP* standardisation enables one to derive dimensionless FDCs to be used for regionalisation, and to predict a dimensional curve, which is ultimately what practitioners really need for addressing the water problem at hand, simply by multiplying the dimensionless FDC by MAP and catchment area. The discriminant between the two ways resides in the fact that the uncertainty associated with predictions of MAP is generally significantly smaller than the uncertainty associated with predictions of MAF for ungauged sites, in virtue of the large availability of raingauges and the accuracy of geostatistical procedure for interpolating point observations (see e.g. Brath et al., 2003; Castellarin et al., 2004a).

Concerning the practical computation of empirical TND values, that is TND₁ or TND₂empirical values, the record length generally varies among the available streamgauges. Therefore, before applying 3-(3) one needs to set a maximum duration d_{\max} that can be used in order to compute the TND values consistently for all sites in the region. d_{\max} can-should be set according to the minimum record length in the region (e.g. if the minimum record length in the region is 5 yr, one should-could set $d_{\max} = (5 \times 365)/(5 \times 365 + 1)$).

Once a suitable reference streamflow is selected for performing the standardisation of the curves (i.e. MAF or MAP*), one can easily identify the number of durations m for which the empirical dimensionless streamflow values are lower than 1 (i.e. streamflow values lower then than MAF or MAP*) and compute TND according to 3-(3). For instance, once computed the standard-normal duration z_i associated with each standardised and log-transformed streamflow quantile q_i , Δ_i in 3-(3) can be computed as,

$$\Delta_i = 0.5(z_{i+1} - z_{i-1}) \quad \text{for } i < m \quad (7a)$$

$$\Delta_i = 0.5(z_i - z_{i-1}) \quad \text{for } i = \underline{1}, m. \quad (7b)$$

3.3 Geostatistical interpolation of TND and FDCs

Empirical TND (i.e. TND₁ and TND₂) values are site specific and can be interpolated with geostatistical techniques. Top-kriging can be applied as illustrated in the stepwise description by Skøien (2013) through the suite of R-functions included in the R-package `rtop`, which can be accessed from the Comprehensive R Archive Network (CRAN, <http://cran.r-project>.

org/). The application of Top-kriging formally requires exactly the same steps in both cases (i.e. for empirical TND_1 and TND_2 values). For the sake of brevity, we will recall these steps by referring to the set of empirical TND_1 values only.

The point sample variogram for each standardisation (see Sec. 3.2) can be computed using the binned variogram technique, for which sample points are aggregated in distance classes or bins, under the hypothesis of isotropy, i.e. the variogram does not vary with direction. The sample variogram can then be modelled through a suitable [function-theoretical model](#) (e.g. exponential, Gaussian, spherical, fractal, etc.) ~~among the available theoretical models. Skøien et al. (2006).~~ [Skøien et al. \(2006\)](#) recommend the use of the exponential variogram.

Once the empirical variogram is modelled, the number n of neighbouring stations on which to base the spatial interpolation is set iteratively by the user on the basis of a first set of preliminary analyses, which aim at identifying the n value that produces the most accurate predictions in cross-validation (i.e. for predicting TND values in ungauged locations). This means that the local prediction of TND values, i.e. the computation of ordinary linear system in [2\(2\)](#), depends on n -dimensional kriging weights.

We assume in our study that the n kriging weights that are computed for predicting TND in ungauged locations can also be adopted for predicting the flow-duration curve in the same locations as a weighted average of n standardised empirical curves as,

$$\hat{\psi}(x_0, d) = \sum_{i=1}^n \lambda_i \psi(x_i, d) \quad d \in (0, 1) \quad (8)$$

where λ_i are the Top-kriging weights resulting from TND interpolation, $\psi(x_i, d)$ indicates the standardised empirical FDC for site x_i , that is a flow-duration curve in which streamflow quantiles are divided either by MAF or by MAP^* , $\hat{\psi}(x_0, d)$ stands for the standardised FDC predicted for site x_0 ~~and over~~ the entire duration domain d , n is the number of neighbouring sites in the vicinity of the site of interest. [It is worth noting that while FDC predictions are performed by using empirical standardised FDCs as a whole \(i.e. the prediction is performed over the entire duration interval\), the computation of empirical TND values does not consider lower durations \(see details in Sec. 2.2\). Therefore, it will be particularly interesting to analyse the performance](#)

of the proposed procedure for predicting high flows. We will assess ~~this-our~~ assumption relative to a study area which was extensively analysed in previous studies in the context of regionalisation of FDCs (see e.g. Castellarin et al., 2004a, 2007).

4 Study area and data

The study region includes 18 unregulated catchments, which previous studies describe as a rather heterogeneous group of sites in terms of physiographic and climatic characteristics (see e.g. Castellarin et al., 2007, 2004a). Daily streamflow series were obtained for all basins from the streamgauges belonging to the former National Hydrographic Service of Italy (SIMN) over the time period 1920–2000. The length of the observed series ranges from 5 to 40 yr (average record length: 18 yr). Also, the empirical MAP value relative to each ~~one~~ of the 18 catchments ~~were~~ was estimated using data collected from a rather dense raingauge network (i.e. 1 raingauge per $\approx 50 \text{ km}^2$) during the same time-interval of daily streamflow observations.

Empirical FDCs were constructed from the daily streamflow series for the 18 catchments as described in Sec. 3.1. Empirical TND_1 and TND_2 values were computed for each catchment according to standardisations described in Sec. 3.2, and are illustrated in ~~the two maps of~~ Fig. 3. As shown in the left panel of Fig. 3, empirical TND_1 values increase moving from south-east to north-west. This outcome reflects the lower perviousness of the northern catchments, which are then less capable of storing water volumes and consequently are characterised by steeper empirical FDCs. ~~Figure 3 (right) illustrates empirical TND_2 values obtained for the study catchments.~~ Moving from south-east to north-west, one can note for TND_2 (right panel of Fig. 3) similar patterns to those observed for TND_1 values, i.e. TND values tend to increase along the SE–NW direction. On the one hand this general behaviour suggests that in our case study Mean Annual Flow (MAF) is largely controlled by precipitation, on the other hand, karst phenomena associated with the presence of fractured limestones result in an increase of TND_2 for the Southern catchments, i.e. sites 3006, 3003 and 3002, for which subsurface flows play a significant role.

Table 1 illustrates the variability over the study region of catchment area A (km^2), mean annual flow MAF ($\text{m}^3 \text{s}^{-1}$), mean annual precipitation MAP (mm), MAP* ($\text{m}^3 \text{s}^{-1}$), empirical TND_1 (-) and TND_2 (-) values, by reporting the minimum, mean and maximum values, together with the 1th, 2nd and 3rd quartiles of each index.

5 Analysis and results

5.1 Prediction of FDCs in cross-validation

We will refer to the proposed approach as TNDTK (i.e. Total Negative Deviation Top Kriging) in the [reminder-remainder](#) of the paper. This section illustrates in detail the application of TNDTK in cross-validation, describing the accuracy of the procedure when applied in ungauged basins.

5.1.1 Standardisation by MAF

The application of TNDTK to the prediction of FDCs standardised by MAF requires the preliminary application of Top-kriging to TND_1 values, which we performed by calculating binned sample variogram first, and then by modelling binned empirical data with a [4-parameter 5-parameter “modified”](#) exponential theoretical variogram ([see details in Skøien et al., 2006](#)). [The four \(a combination of exponential and a fractal model, see details in Skøien et al., 2006\)](#). [As an example, Figure 4 shows the differences between fitted variograms by either using no bins \(i.e. point variogram\) or by binning groups of pairs of catchments with different combinations of drainage areas. The five](#) parameters were fitted through the Weighted Least Squares (WLS) regression method from Cressie (1985). Top-kriging was then iteratively applied to the study catchments in cross-validation to identify the most suitable number of neighbours n . Preliminary iterations indicated $n = 6$ as [the optimal number of gauging stations: a good candidate for the study area \(see Sec. 5.1.2\)](#).

We then used the kriging weights obtained for predicting TND_1 in cross-validation at each and every site to estimate dimensionless FDCs. We resampled In order to assess the prediction accuracy and to compare the performances of different models we choose to resample each curve using $p = 20$ points equally spaced in the log-normal representation (see Sec. 2.2 and Fig. 2), ~~choosing~~ adopting $d_1 = 0.00135$ as lower bound and $d_{20} = 0.9986$ as the upper one (d_1 and d_{20} values ~~were~~ selected by referring to the minimum record length in the regional sample, i.e. 5 yr). Predictions were performed through a weighted average, as expressed in Eq. (8)(8), using the optimal Top-kriging cross-validation weighting scheme, i.e. λ_i with $i = 1, \dots, n$, where $n = 6$.

As ~~anticipated, a comprehensive~~ mentioned in Sec. 1, a leave-one-out cross-validation procedure (LOOCV) was performed in order to simulate ungauged conditions at each and every gauged site in the study area and to quantitatively test the reliability and robustness of TNDTK for predicting FDCs in ungauged basins

(see examples in Kroll and Song, 2013; Salinas et al., 2013; Wan Jaafar et al., 2011; Srinivas et al.,

The LOOCV that can be summarised by the following steps:

1. empirical and theoretical variograms are computed using the entire dataset of TND_1 values;
2. one of the gauging station, say s_i , is removed from the set of available stations;
3. a Top-kriging regional model for predicting TND_1 values is developed using the remaining $N_{\text{site}} - 1$ sites;
4. TND_1 is predicted for site s_i ~~by referring to~~ as a weighted average of the empirical values computed for $n = 6$ neighbouring stations (see e.g. Fig. 5);
5. the weighting scheme computed in step 4 is then used to predict a standardised FDC for site s_i through Eq. (8)(8);
6. steps from 2 to 5 are repeated $N_{\text{site}} - 1$ times.

The accuracy of the cross-validated standardised FDCs was scrupulously assessed by means of several performance indices and diagrams, which are illustrated in detail in Sec. 5.3. The algorithm described above is tailored for the proposed procedure, TNDTK, but one can implement and apply similar resampling procedures to any regional model for simulating ungauged conditions. ~~The technicalities of each procedure necessarily reflect the particular regional model being considered, but the rationale is the same: (i) drop all of the hydrometric information collected at a given streamgauge, s_i ; (ii) identify the regional model; (iii) use the regional model to predict the FDC at site s_i ; (iv) repeat steps (i)–(iii) by considering in turn each one of the remaining $(N_{\text{site}} - 1)$ sites (see Castellarin et al., 2007, and references therein for further details).~~

5.1.2 Standardisation by MAP*

Top-kriging was applied also to predict empirical TND₂ values as well as FDCs standardised by MAP*. The number of neighbouring stations n , theoretical variogram, and fitting procedure were the same as for standardisation based on MAF. ~~Also in this case each standardised FDC was resampled on 20 equally-spaced points in the log-normal representation, adopting the interval $[d_1, d_{20}]$. We used and~~ We used a LOOCV analogous to the one described above (i.e. standardisation by MAF) in order to identify the weighting scheme to be used for simulating ungauged conditions for all of the study basins.

Furthermore, in order to obtain dimensional prediction, each estimated curve $\hat{\psi}(x_0, d)$ was ~~than~~ then transformed into a dimensional FDC, as

$$\hat{\Psi}(x_0, d) = \hat{\psi}(x_0, d) \text{MAP}^*(x_0) \quad \text{with } d \in [d_1, d_{20}] \quad (9)$$

where $\text{MAP}^*(x_0)$ indicates the local MAP* value.

5.2 Reference regional models of FDCs

The same gauged stations and data considered herein were analysed in previous studies that developed regional models of FDCs (see Castellarin et al., 2004a, 2007). This enabled us to

identify for both TNDTK applications two different reference regional models for comparing the performance of the approaches. We report here-below a brief description of such regional models.

5.2.1 Standardisation by MAF

TNDTK predictions of dimensionless FDCs were compared against the dimensionless curves predicted by two reference regional models, which we also applied in cross-validation through a LOOCV procedure:

KMOD

K model (or KMOD) is a statistical regionalisation model developed by Castellarin et al. (2007) that uses the 4-parameter unit-mean kappa distribution as parent distribution for representing standardised FDCs (see e.g. Hosking and Wallis, 1997). Three parameters, namely the parameter of location and the two shape parameters, were estimated by applying an ordinary least squares (OLS) regression algorithm. The scale parameter is derived as a function of the previous three under the hypothesis that the mean of the distribution is equal to one. Castellarin et al. (2007) regressed the parameters estimates against a suitable set of catchment descriptors through a stepwise-regression procedure in order to enable the estimation of the kappa distribution in ungauged sites. KMOD is therefore a traditional parametric regional model which we adopted as the benchmark regional model for predicting standardised FDCs (see for details Castellarin et al., 2007).

MEAN

MEAN is a simple approach to regionalisation, which neglects the physiographic and climatic heterogeneities of the study area, and predicts the standardised FDC for any ungauged site in the region as the average of all available standardised FDCs. We adopted MEAN as a baseline model due to its crude assumption and the resulting low-level accuracy.

5.2.2 Standardisation by MAP*

TNDTK predictions of dimensional FDC were compared with the predictions resulting from two benchmark models, both applied in cross-validation:

LLK

This model, based on an index-flow approach (see Castellarin et al., 2004b), adopts a two-parameter log-logistic (LL) distribution as a suitable distribution for describing the empirical frequency of the annual flow series (i.e. index-flow) and a four-parameter kappa (K) as the parent distribution for dimensionless daily streamflow frequency. Parameters of both distribution were estimated using the routine based on L-moments developed by Hosking and Wallis (see Hosking and Wallis, 1997), re-estimated through a constrained sequential quadratic programming optimisation procedure aimed at minimising the squared differences between theoretical and empirical nonexceedence probabilities, and then regressed against a suitable set of catchment descriptors through a stepwise-regression procedure. More details can be found in Castellarin et al. (2007).

KMOD

Same as KMOD for dimensionless FDCs prediction, but using a multiregression regional model to predict MAF as a function of a suitable set of catchment descriptors in ungauged basins (see e.g. Castellarin et al., 2007 for details).

5.3 Performance indices

TNDTK performance in cross-validation is analysed for both standardisation methods (MAF and MAP*) and compared with the results of reference regional models through several performance indices and diagrams. A deep analysis of model performances in terms of relative prediction residuals, i.e. relative errors between modelled and empirical values (with sign), is presented through error-duration curves. The curves show relative residuals against duration

arranged in gray nested bands containing 50, 80 and 90 % of relative residuals, respectively, while a solid line illustrates the progression with duration of the median residual (**BIAS**). Also, we use as performance descriptors the scatterdiagrams between cross-validated and empirical streamflow quantiles associated with the same duration. On the basis of the same information, NSE (Nash & Sutcliffe Efficiency) indices for each model are computed, both for natural and **in**-log-transformed streamflows. Such diagrams and indices **enhance the overall residual distribution** provide a complete and exhaustive representation of the performance of each model in cross-validation for the entire streamflow regime, from low durations (high-flows and floods) to high ones (droughts), **at a regional scale**.

Concerning the performances of the model at each site, and in particular the assessment of the number of sites for which TNDTK is more reliable then than the selected reference regional models, we adopt a comprehensive error index derived from the distance between predicted and empirical FDCs proposed in Ganora et al. (2009):

$$\delta_{\text{mod}} = \sum_{k=1}^p |q_{k,\text{emp}} - \hat{q}_{k,\text{mod}}| \quad (10)$$

where $p = 20$ resampled points, while $q_{k,\text{emp}}$ and $\hat{q}_{k,\text{mod}}$ stand for the empirical and predicted streamflow quantiles (dimensionless or dimensional, depending on the application) ranked at the k th duration.

5.4 Results

5.4.1 Standardisation by **MAF-dimensionless** MAF: dimensionless FDCs

Figure 5 (left) reports empirical TND_1 values against their Top-kriging predictions in cross-validation. The overall NSE is 0.81. In the same figure one can observe a poor prediction (i.e. significant underprediction) for site 3701, which can be interpreted as a result of the very high empirical TND value obtained for that site (site 3701, $\text{TND}_1 = 9.8[-]$, $A = 605[\text{km}^2]$), the largest in the study region.

~~TNDTK Concerning the~~ predictions of standardised FDCs ~~show excellent results from flood (low duration) to low flows (high duration) for the set of global performance indices and diagrams.~~

The ~~the~~ error-duration curves of Fig. 6 clearly shows that TNDTK significantly outperforms KMOD and MEAN: the distribution of relative residuals plotted against duration is characterised by narrower bands (50, 80 and 90 % of the relative errors) for the entire duration interval, even though this behaviour is more marked for ~~low than for high~~ lower durations. The progression with duration of the median residual (black thick line) in the same figure highlights unbiasedness being close to zero for the entire duration interval. Scatterdiagrams between predicted and observed standardised flows indicate high accuracy of TNDTK, with $NSE = 0.958$ and $LNSE \simeq 0.96$, the latter computed for log-flows. MEAN and KMOD are associated with lower NSE and LNSE values.

Finally, Fig. 7 presents the overall absolute error for each site. In particular in Fig. 7 scatterdiagrams of δ_{mod} are illustrated in two panels, where the ~~x-axes~~ x-axes reports errors computed for the proposed model (TNDTK) while the ~~y-axes~~ y-axes reports in turn errors from reference models. In this representation an equivalence between model performances is represented by the solid bisecting line ~~;~~; hence if one point falls in the top-left above the ~~1:1 line~~ 1:1 line TNDTK provides better predictions ~~then than~~ the reference model, otherwise if it falls below the ~~1:1 line~~ 1:1 line. Figure 7 clearly shows that KMOD is less ~~powerfull then~~ accurate than TNDTK for 14 out of 18 sites, while MEAN performs the poorest, with 16 out of 18 sites characterised by higher δ values relative to TNDTK.

5.4.2 Standardisation by MAP* ~~-dimensional~~ : dimensional FDCs

Right panel of Fig. 5 highlights satisfactory performance of Top-kriging for predicting TND_2 values in ungauged basins, NSE value is approximately 0.6, and site 3701 still presents an outlying behaviour for the same reason explained before.

Although the cross-validated predictions of TND_2 ~~values~~ are less accurate than TND_1 ~~ones~~, TNDTK performance for predicting dimensional FDCs is good. Comparing TNDTK with LLK models, Fig. 8 shows for LLK narrower bands for $d < 0.8$, particularly the band illustrating 90 %

of residuals, while in the low-flow-low-flow range (i.e. $0.8 < d < 1$) TNDTK shows slightly better performances, resulting in narrower error bands. The bottom panels in the same figure report the scatterdiagrams of predicted vs. observed dimensional flows, expressing the goodness and reliability of TNDTK when used for predicting dimensional FDC on the basis of MAP. Even though TNDTK shows an $NSE = 0.914$, which is lower than the NSE value associated with LLK and equal to KMOD one, TNDTK is associated with the highest LNSE value ~~TNDTK is associated with the highest value of LNSE~~ (i.e. 0.922), which highlights the very good performance of TNDTK for low-flows. Figure 9 confirms good performance of TNDTK against LLK and KMOD, showing in both cases ~~more accurate predictions~~ better accuracy for 10 out of 18 catchments. Also, among the 8 catchments for which LLK and KMOD perform better than TNDTK, it is worth nothing that performances are practically ~~the same of~~ coincident with TNDTK in 2 cases for LLK ~~and~~ (i.e. sites 3006 and 2201) and 3 cases for KMOD ~~(i.e. sites 1004, 2101 and 3006)~~.

6 Discussion and future work

5.1 Sensitivity analysis

5.2 ~~Is Top-kriging suitable for predicting long-term FDCs?~~

5.1.1 Consistency of the kriging weighting scheme

The ~~cross-validation of TNDTK shows that the proposed procedure~~ core assumption of the proposed method is that Top-kriging weights λ s identified for predicting TND values can be used to weight empirical FDCs. In order to test and validate this assumption we analysed the relationship between such weights and the degree of dissimilarity between empirical FDCs. In particular, we computed for each pair of catchments a dissimilarity metric $\beta_{i,j}$, proposed by

Ganora et al. (2009), which can be expressed as follows for catchment i and j :

$$\beta_{i,j} = \sum_{k=1}^{365} |q_{i,k} - q_{j,k}| \quad (11)$$

where 365 is a reasonable resampling scheme and $q_{i,k}$ and $q_{j,k}$ are the streamflow values associated with duration $d_k = \frac{k}{365+1}$ for site i and j respectively. If our assumption is correct, large β values (i.e. dissimilar curves) should be associated with small λ values, and vice-versa. Top-kriging takes into account the nested structure of catchments, therefore where the upstream-downstream correlation occurs (i.e. similar curve with small β) relative high λ value is expected.

Figure 11 (right panel) plots $\beta_{i,j}$ values computed with Eq. (11) for each pair of basins in the study area, with $i, j = 1, \dots, 18$ and $i \neq j$ (i.e. 306 points), against the corresponding $\lambda_{i,j}$ weights obtained by running a TNDTK session with $TND = TND_1$ and, necessarily, a number of neighbours $n = 17$ (i.e. all stations need to be considered if we have to compare $\beta_{i,j}$ with $\lambda_{i,j}$ for $i \neq j$). The figure also highlights the differences between nested (large black dots) and un-nested (gray circles) catchments pairs. The figure clearly proves that the hypotheses are satisfied: (1) weights $\lambda_{i,j}$ show a descending pattern as $\beta_{i,j}$ increase and (2) any nested pair of catchments is associated with a high or very high β value.

5.1.2 Sensitivity to the number of neighbours n

As mentioned in Sec. 5.1.1 and 5.1.2, we set the number of neighbours $n = 6$ in Eq. (8) for performing the prediction of FDCs. We identified this value through a sensitivity analysis, which was carried out by running multiple Top-kriging sessions, each one referring to a different n value. The main outcome of our sensitivity analysis is that the performance of the approach is not dramatically dependent on n , quite the opposite. Figure 10 shows the results of the sensitivity analysis for both standardisations (i.e. MAF and MAP*) obtained in each session in terms of NSE and LNSE for n , ranging from 3 to 17 (i.e. being 18 the total number of catchments for the study area). The left panel refers to dimensionless FDCs (i.e. standardisation by MAF) and shows for $n = 6$ the best trade-off between NSE and LNSE. Nevertheless, NSE

and LNSE are rather high for all n values. Likewise, the right panel refers to the prediction of dimensional FDCs (i.e. standardisation by MAP*) and it shows that performances in terms of NSE are insensitive to n , while in terms of LNSE, we obtain slightly better performances are associated with $n \leq 6$. As a result of the analysis we selected $n = 6$ for all applications for the sake of consistency, even though selecting a different value for n does not impact the results significantly.

5.1.3 Sensitivity to the degree of nesting of the study catchments

From an operational view point it is important to understand if the degree of nesting of the study catchments impacts the performance of the approach. Better performances are to be expected in all those cases in which empirical FDCs can be constructed upstream or downstream the (ungauged) site of interest. In order to quantify this impact we validated TNDTK by removing all catchments that are nested with the catchment of interest. Figure 11 (left panel) shows all nested pairs through a graphical matrix where nested pairs are highlighted with large black dots (catchment IDs are also indicated). First we identified all nested pairs of catchments (i.e. basin-subbasin relationships). Second, we used a cross-validation procedure similar to the procedure described in Sec. 5.1.1, in which, at point 2, we neglected all information collected for the site of interest, but also upstream or downstream that site. We termed this procedure Leave Nested Out Cross-Validation (LNOCV). It is worth noting that LNOCV estimates empirical and theoretical variograms at each and every step of the validation procedure, differently from LOOCV, where they are estimated beforehand once and for all.

We report here only the results referring to the prediction of dimensionless FDCs (i.e. standardisation by MAF). Results obtained relative to dimensional FDCs (i.e. standardisation by MAP*) are analogous. The results, shown in Fig. 12, highlight a slight reduction of performances, with NSE and LNSE indices equal to 0.95 and 0.92 respectively (central panel); also looking at the error-duration bands (left panel in the same figure) the distribution of relative residuals presents slightly wider bands and a larger bias for the median line, especially relative to the high durations (low flows). Moreover, comparing the overall error index for each site produced by the two cross-validations (i.e. LOOCV and LNOCV) (right panel), most of the points (14 out of

18) falls above the solid bisecting line, confirming an impoverished prediction capability of the latest approach. Nevertheless, the detriment of performances associated with LNOCV appears to be limited.

6 Discussion and future work

6.1 Is Top-kriging suitable for predicting long-term FDCs?

The results of the cross-validation show that Top-kriging can be effectively applied in the study region for predicting standardised FDCs (i.e. flow-duration curves divided by an index-flow such as MAF) the mean annual flow, MAF) in the study region. In particular, the interpolation strategy applied in this study, (termed Total Negative Deviation Top-kriging, TNDTK), that is (1) the computation of TND the streamflow index Total Negative Deviation (TND) for empirical standardised FDCs, (2) the modelling of spatial correlation of empirical TND values along the stream network, (3) the identification of a linear weighting scheme for averaging empirical dimensionless FDCs on the basis of the correlation model identified at step (2), results in reliable predictions of standardised FDCs in ungauged sites. The curves predicted in cross-validation are unbiased for the entire duration range (i.e. from high- to low-flows) and the prediction residuals are as small as, or smaller than, the residuals resulting from the application of traditional regionalisation schemes.

Analyzing-Analysing the results in detail, Fig. 6-7 indicates that TNDTK performed significantly worse than the baseline and benchmark regional models in three cases only. The benchmark model KMOD (i.e. KMOD) better predicts the FDC for site 3701 (left panel of Fig. 7). As illustrated in right panel in Fig. 2, site 3701 is associated with the steepest empirical flow duration curve of the study region and therefore the highest empirical TND value (see Table 1 and Figs. 1 and 5). This is a result of the very limited permeability of the catchment, which

The core assumption of Top-kriging hypothesises is that hydrological similarity is mainly controlled by spatial proximity, and this may represent an important limitation in some regions where geology and/or morphology have a large impact on streamflows, such that the hydrological

regime of nearby catchments may be quite different. This could in principle explain the poor prediction obtained in the study for site 3701, which is characterised by a very limited permeability (i.e. can be regarded as impervious. The surrounding catchments have higher permeability) relative to the surrounding catchments, and, consequently, flatter empirical FDCs that produce a biased interpolation. While a much steeper empirical FDC than the neighbouring sites. Conversely, information on permeability is explicitly incorporated in the multiregression models included in KMOD (see e.g. Castellarin et al., 2007), ~~the degree of permeability of the catchment is not considered in the kriging procedure which is mainly driven by spatial proximity. The.~~ Furthermore, the baseline model MEAN significantly outperforms TNDTK for sites 2502 and 801, and this result can be explained by noticing that both sites are associated with empirical standardised curves that are well represented by the average standardised FDC for the study region (see right panel in Fig. 2) (see right panel in Fig. 2 and Castellarin, 2014), that is the curve associated with the baseline regional model (MEAN) in cross-validation.

~~This positive outcome derives from the main features of TNDTK, that are associated with several advantages. Aside from peculiar cases highlighted above, TNDTK shows a high performance in cross-validation that is likely to result from several advantages of the proposed procedure.~~ TNDTK dispenses with the critical phase of delineating hydrologically homogeneous pooling group of sites (see Castellarin et al., 2004a) by exploiting the spatial correlation structure of the streamflow regime (see Archfield and Vogel, 2010). ~~Also~~ Nevertheless, the approach does not require to set up multiregression models for estimating the parameters of a mathematical expression (e.g. a theoretical frequency distribution) controlling the shape of the curve, which are often associated with a large uncertainty and limited robustness (see Castellarin et al., 2007); TNDTK predicts the shape of the curve for an ungauged basin through a non-parametric procedure as a weighted average of empirical standardised FDCs (e. g. Smakhtin et al., 1997; Ganora et al., 2009). The weighting scheme also ensures for the predicted curve a non-increasing (i.e. monotone) relationship between streamflow and duration, which is one of the main properties of flow-duration curves.

The study also points out that TNDTK can be used for predicting dimensional FDCs in ungauged sites on the basis of a minimal set of hydrological information, that is (a) empirical

FDCs for a group of ~~gauges~~-gauged basins and (b) an estimate of Mean Annual Precipitation (MAP) for all gauged basins in the region, as well as for the target ungauged basin. Even though TNDTK does not show a clear supremacy relative to more traditional approaches (see Figs. 8 and 9), it has to be highlighted that its application is rather straightforward and does not require any subjective choice, which, together with the fact that the procedure can be implemented with a limited amount of input data, makes TNDTK a very interesting alternative for predicting dimensional FDCs.

6.2 Future analyses

Our study is evidently a preliminary analysis, which tackles the exploration of geostatistical approaches for predicting FDCs. Therefore, the results of our study open up several possible research avenues. In particular, we focus on the prediction of long-term steady-state FDCs, on the basis of Period-of-Record (POR) empirical FDCs. Applicability of TDNTK to the prediction of annual FDCs for typical hydrologic years, as well as for particularly wet or dry years (see e.g. Vogel and Fennessey, 1994; Castellarin et al., 2004b), is an open problem that needs to be specifically and quantitatively addressed.

Evidently, the proposed approach needs to be further investigated in other geographical contexts. In particular, the application of TNDTK for predicting dimensional FDCs on the basis of catchment-scale MAP values deserves some further tests that aim at verifying its suitability for significantly different climatic conditions (e.g. arid regions, alpine catchments, etc.), in which the streamflow regime is not heavily controlled by the rainfall regime, as for the considered case study.

Finally, we propose to summarise empirical flow-duration curves through the index TND, which expresses the total negative deviation of the curve from a reference streamflow value. ~~Although this index proved to be very informative on the similarity of empirical flow-duration curves constructed for the study region, its validity needs a deeper investigation. More importantly~~ We are aware that the proposed procedure needs to be further tested in different geographical and climatic contexts before its general validity can be acknowledged. Also, we believe that the TND index identified in this study incorporates a worth of hydrological information and has the

potential to be extremely useful in a number of hydrological problems other than the prediction of FDCs, such as catchment classification (see Wagener et al., 2007; Di Prinzio et al., 2011) or regionalisation studies (Laaha and Blöschl, 2006; Gaál et al., 2012). Future analyses will specifically address these points. Moreover, future analyses should focus on the identification of a global indicator of the similarity between FDCs to be used to analyze-analyse and model geographical correlation between the empirical curves themselves, this would enable one to base the definition of the linear weighting scheme on a more comprehensive and descriptive indicator of the streamflow regime, instead of the semivariogram constructed for a point index (i. e. TND).

7 Conclusions

This study explores the possibility to extend the application of Top-kriging, which is generally used for spatial interpolation of point streamflow indices (e.g., estimated flood quantiles, low-flow indices, temperature, etc.), to the prediction of period-of-record flow-duration curves (FDCs) in ungauged basins. Top-kriging is used in this study to geostatistically interpolate standardised FDCs along the streamnetwork-stream network of a broad geographical area in Central-Eastern Italy. We identified-identify the linear weighting typical of any kriging procedure by modeling the spatial correlation structure of an empirical streamflow index, which was shown in the study to be particularly useful in describing the daily streamflow regime of a given catchment. In particular, we defined-define the index, which we termed-term Total Negative Deviation (TND), as the overall negative deviation of an empirical FDC relative to a reference streamflow-value used for the standardisation of the empirical-curves.

We considered-in-the-study-curve itself. We consider two different reference streamflow values, that is the Mean Annual Flow (MAF) and catchment-scale Mean Annual Precipitation times the drainage area of the catchment (MAP*). By applying Top-kriging along the stream-network to the spatial distribution of empirical TND values, the former standardisation (, and we use these streamflow values for standardisation of the empirical FDCs prior to regionalisation. The standardisation based on MAF)-enabled-enables us to develop a -Top-kriging-based regional model of dimensionless FDCs, while we-used-the-latter-(the standardisation based on MAP*)

[enables us](#) to predict dimensional flow-duration curves in ungauged basins [via Top-kriging](#). The two regional estimators were cross-validated and compared in terms of prediction performances with other regional models of dimensionless and dimensional [flow-duration](#) [flow-duration](#) curves that were previously developed for the study area. The comparison highlights [the superior good](#) performances of the proposed procedure ([which we termed](#) Total Negative Deviation Top-kriging, (TNDTK) relative to traditional regional models [for predicting standardised FDCs](#). [FDCs predicted with TNDTK are unbiased independently of the considered duration](#), and [prediction residuals are significantly smaller than those associated with traditional regionalization procedures, in particular if high durations are considered](#). [TNDTK is unbiased throughout the entire duration interval and characterised by particularly small residuals for high durations](#) (i.e. [improved predictions of](#) low-flows). [Also, our study points out that applying TNDTK to regionalise FDCs standardised by MAP* enables one to predict dimensional FDCs in ungauged basins on the basis of a minimal set of hydrological information: \(a\) empirical FDCs for a group of gauged basins and \(b\) an estimate of catchment-scale Mean Annual Precipitation \(MAP\) for all gauged basins in the region, as well as for the target ungauged basin](#). Moreover, the prediction accuracy of TNDTK is similar to, or higher than, more complex [regionalization](#) [regionalisation](#) approaches that use multiregression models [that incorporate](#) [incorporating](#) information on the permeability, morphology, climate, etc. of the catchment, [which](#). [This result](#) seems to confirm the value of spatial proximity relative to catchment attributes ([see e.g. Merz and Blöschl, 2005](#)) when hydrological predictions in ungauged basins are concerned ([see e.g. Merz and Blöschl, 2005](#)).

Our study is indeed a preliminary analysis, and we are aware that the proposed procedure needs to be further tested in different geographical and climatic contexts before its general validity can be acknowledged. Nevertheless, we believe that this study further highlights the potential of Top-kriging by showing how it can be easily adapted for predicting flow-duration curves. Also, we believe that the TND index identified in this study incorporates a worth of hydrological information and has the potential to be extremely useful in a number of hydrological problems other than the prediction of FDCs, such as catchment classification (see Wagener et al., 2007; regionalization studies (Laaha and Blöschl, 2006; Gaál et al., 2012), future analyses will specifically address this point.

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Table 1. Study catchments: variability of drainage area (A), Mean Annual Flow (MAF), Mean Annual Precipitation (MAP), rescaled mean annual precipitation (MAP*) and empirical TND₁ and TND₂ values; table lists and length of the ~~minima~~observed streamflow series (Y); ~~minimum~~, ~~maxima~~maximum, ~~means~~mean, 1st, 2nd (median) and 3rd quartiles of the sample distributions.

	A [km ²]	MAF [m ³ s ⁻¹]	MAP [mm]	MAP* [m ³ s ⁻¹]	TND ₁ [-]	TND ₂ [-]	<u>Y</u> [yr]
min	61	1.49	918.1 <u>918</u>	2.17	1.59	1.25	<u>5</u>
1st Qu.	104	2.63	1079.0 <u>1079</u>	3.60	2.76	4.38	<u>8.5</u>
median	164	3.83	1123.0 <u>1123</u>	5.99	3.82	5.78	<u>11.5</u>
mean	330	6.51	1118.0 <u>1118</u>	11.69	4.52	6.11	<u>18.1</u>
3rd Qu.	562	7.54	1162.0 <u>1162</u>	17.53	5.74	7.55	<u>26</u>
max	1044	21.29	1298.0 <u>1298</u>	37.07	9.83	13.21	<u>40</u>

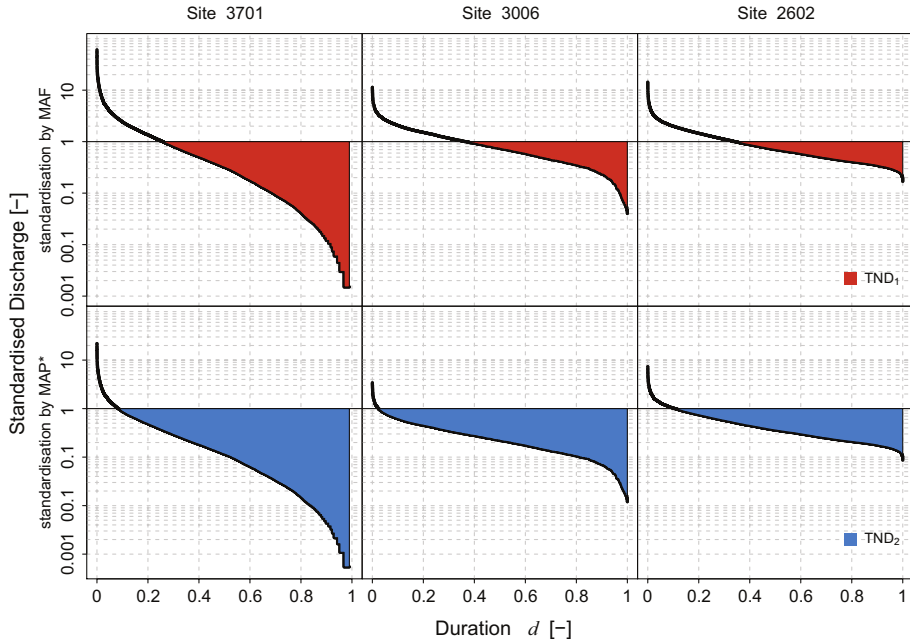


Fig. 1. Total Negative Deviation (TND, filled area) for three catchments with different hydrological behaviours (see Sec. 4). Top panels: TND_1 (red area) for an empirical FDC (black tick-thick line) standardised by Mean Annual Flow (MAF); bottom panels: TND_2 (blue area) for an empirical FDC (black tick line) standardised by $MAP^* = MAP \cdot A \cdot CF$, where MAP is the Mean Annual Precipitation, A is the drainage area and CF is a unit-conversion factor.

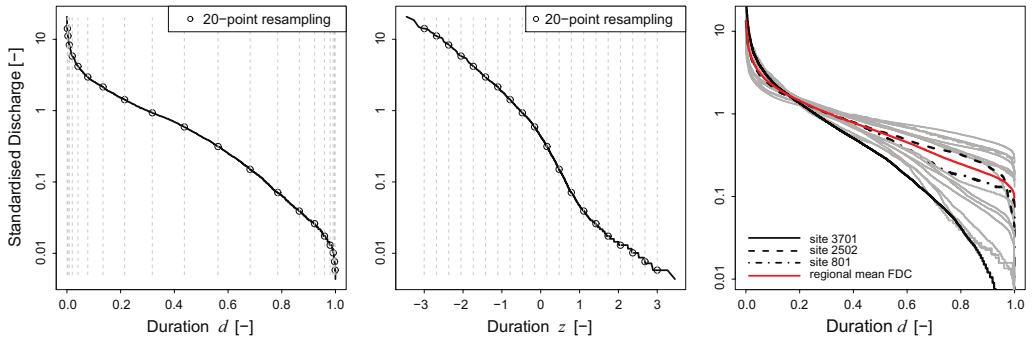


Fig. 2. FDC representations: log-natural scale (left), log-normal scale (center); the panels also show a resampling of the empirical curve (circles) which employs 20 equally-spaced points equally-spaced in the standard-normal space; standardised empirical FDCs for the study region (right), FDC for sites 3701, 801, 2502 and regional mean FDC are highlighted.

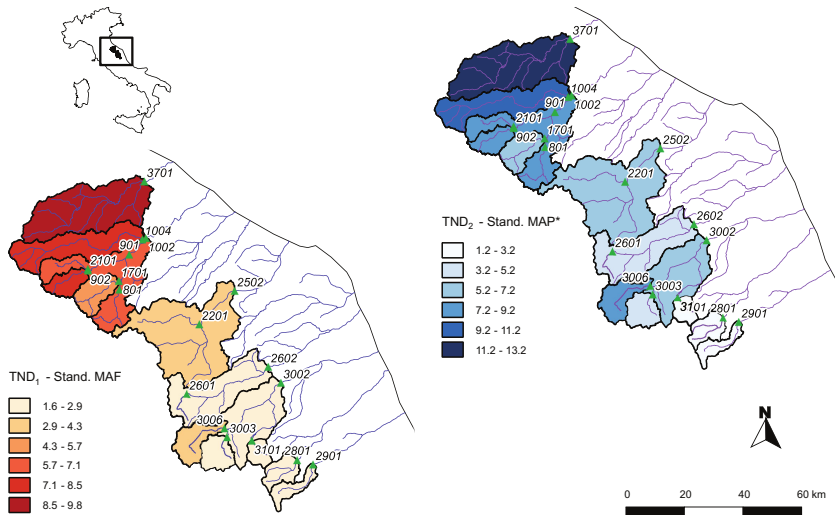


Fig. 3. Empirical TND₁ and TND₂ values for the study catchments.

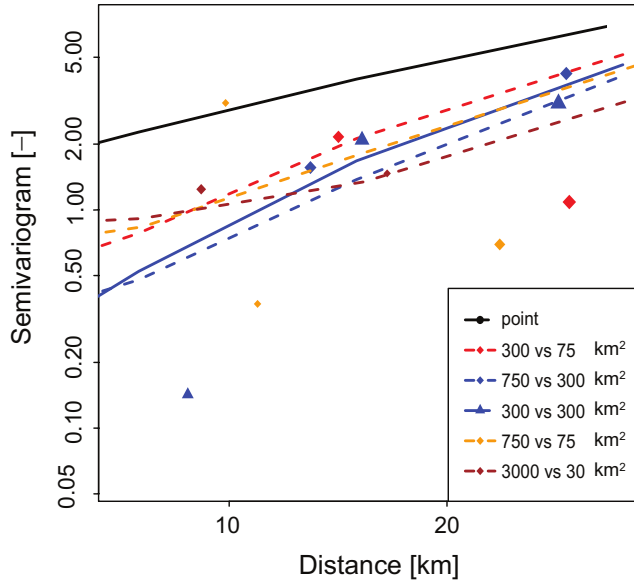


Fig. 4. Empirical and theoretical semivariograms from TND_1 values. Black line shows the fitted point variogram. Colour markers and lines show empirical and fitted variograms (empirical variograms are computed by binning catchment pairs for different combinations of catchment areas, e.g. $\approx 300 \text{ km}^2$ vs $\approx 75 \text{ km}^2$).

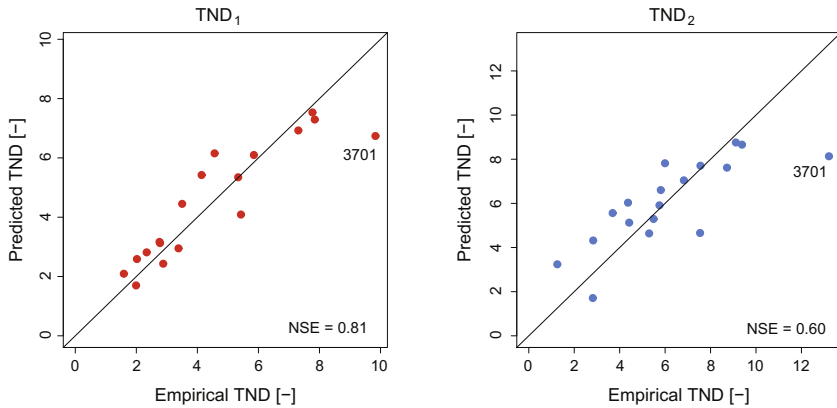


Fig. 5. Top-kriging predictions of TND_1 and TND_2 values in cross-validation, predictions for site 3701 are highlighted.

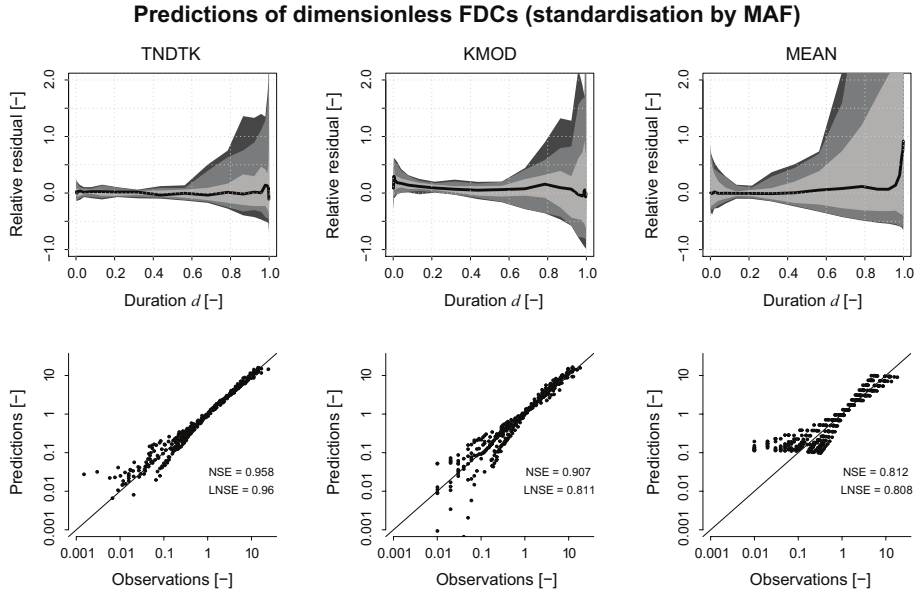


Fig. 6. Cross-validation of regional models: MEAN (right), KMOD (center), TNDTK (proposed approach, left); error-duration **curves** **bands** reporting the profile of the median relative error (thick black line) and the bands containing 50 %, 80 % and 90 % of the relative errors (grey nested bands) as a function of duration (top); empirical vs. predicted standardised streamflows (bottom).

Predictions of dimensionless FDCs (standardisation by MAF)

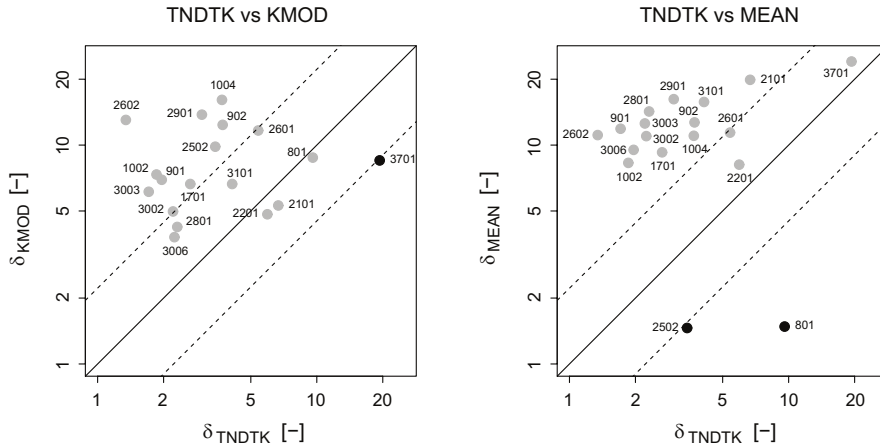


Fig. 7. Comparison between TNDTK, MEAN and KMOD models in terms of distances between empirical and predicted FDCs, δ_{mod} (where mod stands for TNDTK, MEAN or KMOD); values of δ_{TNDTK} are reported against values of δ_{KMOD} (left) or δ_{MEAN} (right) for each **considered study** basin; the solid line represents the ratio **1:1** between the errors, while **in the area outside the** dashed lines delimit the **areas where** errors for the TNDTK model are twice **as large as** the MEAN or KMOD ones **and, or** vice versa. Points above the solid line represent curves better estimated by TNDTK; points above the top dashed line represent curves **that are** much better estimated by TNDTK (see also Ganora et al., 2009, Fig. 8); sites 3701 and 801 are highlighted.

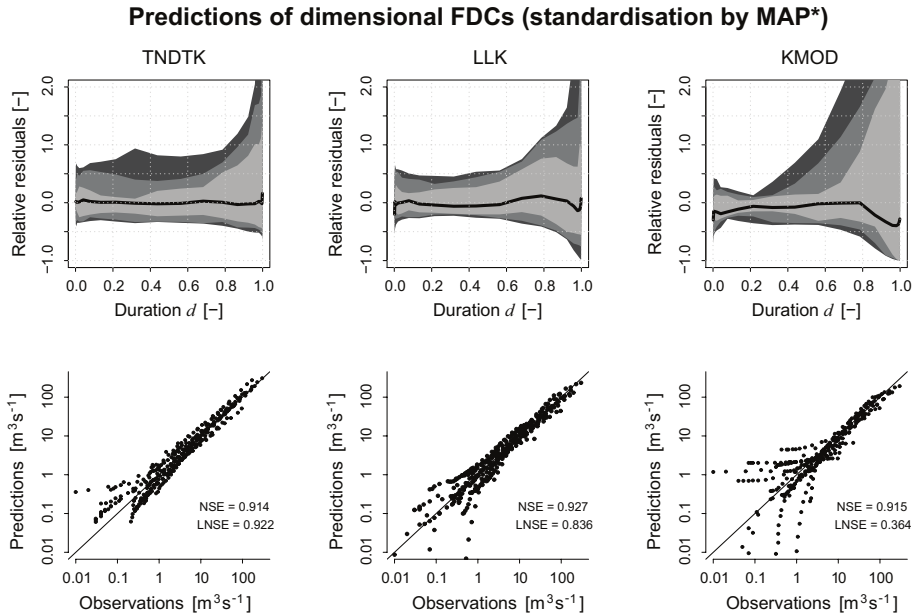


Fig. 8. Cross-validation of regional models: KMOD (right), LLK (center), TNDTK (proposed approach, left); error-duration [curves](#) [bands](#) reporting the profile of the median relative error (thick black line) and the bands containing 50 %, 80 % and 90 % of the relative errors (grey nested bands) as a function of duration (top); empirical vs. predicted dimensional streamflows (bottom).

Predictions of dimensional FDCs (standardisation by MAP*)

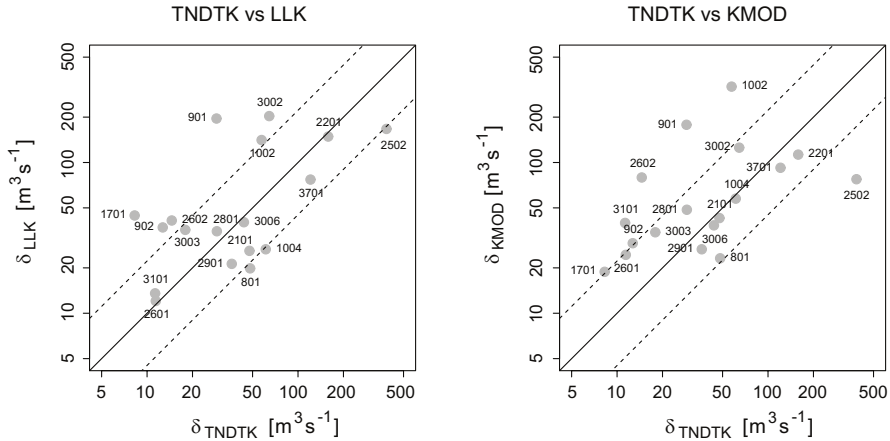


Fig. 9. Comparison between TNDTK, KMOD and LLK models in terms of distances between empirical and predicted dimensional FDCs, δ_{mod} (where mod stands for TNDTK, KMOD or LLK); values of δ_{TNDTK} are reported against values of δ_{LLK} (left) or δ_{KMOD} (right) for each **considered study** basin; the solid line represents the ratio 1 : 1 between the errors, while **in the areas outside the** dashed lines delimit the areas where errors for the TNDTK model are twice **as large as** the LLK or KMOD ones **and, or** vice versa. Points above the solid line represent curves **that are** better estimated by TNDTK; points above the top dashed line represent curves much better estimated by TNDTK (see also Ganora et al., 2009, Fig. 8).

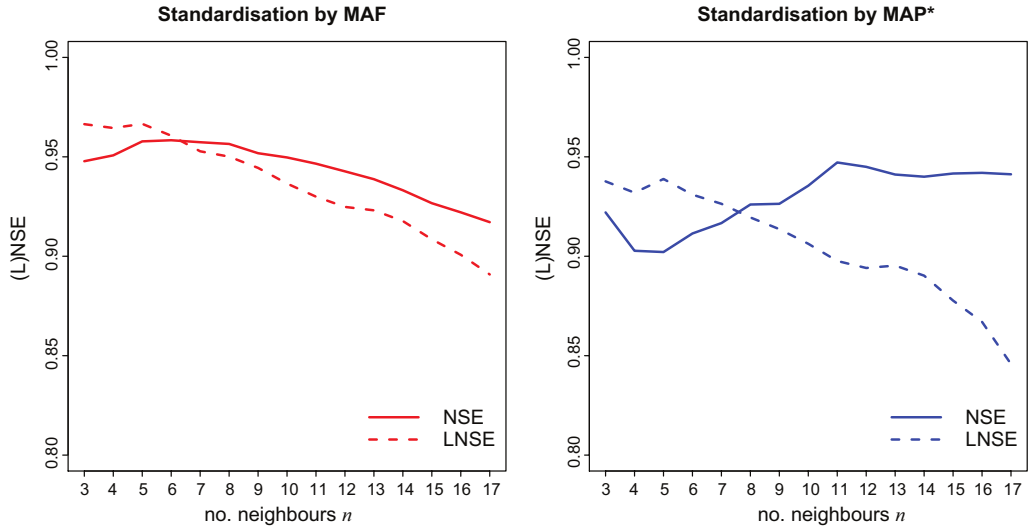


Fig. 10. Nash & Sutcliffe Efficiency for natural (NSE, filled lines) and log-transformed (LNSE, solid lines) streamflows plotted against the number n of neighbouring stations used for the interpolation. Left panel shows the predictions results for dimensionless FDCs (i.e. MAF standardisation), while the right panel reports the results for dimensional FDCs (i.e. MAP*).

Nested structure of the study area

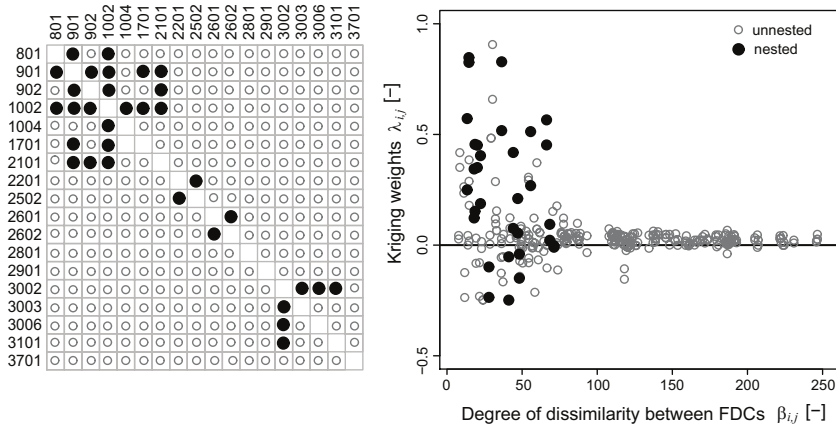


Fig. 11. Nested structure of the study area: (left) black dots identify nested pairs (i.e. basin-subbasin relationships); (right) Top-kriging weights $\lambda_{i,j}$ obtained for predicting TND_1 vs. the corresponding degree of dissimilarity between empirical FDCs for sites i and j , $\beta_{i,j}$, nested pairs are highlighted.

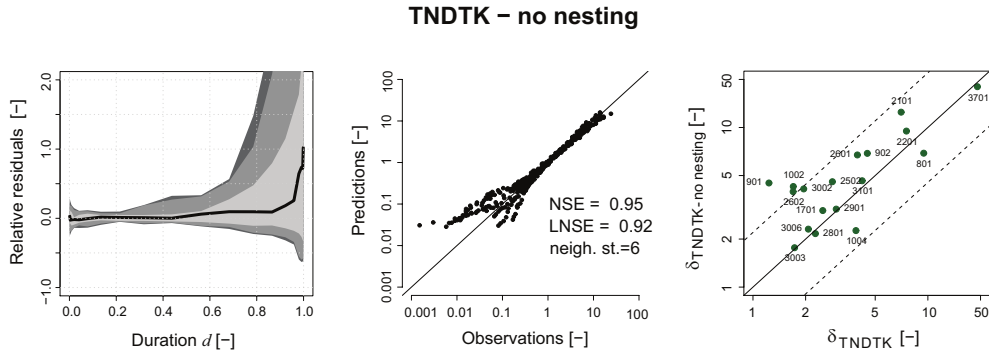


Fig. 12. Results of Leave Nested Out Cross-Validation (LNOCV): error-duration bands reporting the profile of the median relative error (thick black line) and the bands containing 50%, 80% and 90% of the relative errors (grey nested bands) as a function of duration (left); empirical vs. predicted standardised streamflows (center); comparison of overall errors between empirical and predicted dimensionless FDCs, values of δ_{TNDTK} (Sec. 5.1.1) are reported against values of $\delta_{\text{TNDTK-no nesting}}$ (right).