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The legacy of STAHY: Milestones, achievements, challenges, and open problems in statistical hydrology

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Abstract

Statistical tools are crucial for a variety of hydrological applications, whether to model processes and enhance understanding and knowledge or to design infrastructure systems. Given the rapid evolution of statistical methods and the need for a solid theoretical foundation for their correct application, a multidisciplinary community (STAHY-WG) aggregated under the IAHS umbrella to contribute to this research field. Now, after more than fifteen years since its inception, this paper summarizes the main achievements of this productive community collaboration in four (of many) branches of statistical hydrology: extreme value analysis, multivariate analysis, time series analysis, and regionalization. The aim is to provide an overview of recent developments, offer practical suggestions (e.g., software packages), and outline future challenges to support scientists and practitioners in their endeavors within the realm of statistical hydrology studies.

Keywords: ICSH, STAHY, extreme value analysis, GEV, metastatistical distributions, copula function, time series analysis, FARMA model, changing point analysis, rainfall simulations, regionalization

1. Introduction

Statistical methods for analysis, synthesis, and modeling of hydrological data have a long history and continue to be an intense research topic. Such tools have proved to be very effective and useful in numerous applications. The effectiveness of the statistical description of hydrological processes reflects the enormous complexity of the hydrological systems, which often makes a purely deterministic description ineffective (Koutsoyiannis, 2021); indeed, all hydrologic processes reflect a combination of both deterministic and stochastic elements (Vogel, 1999). A clear exemplification is provided by Farmer and Vogel (2016), who document systematic

bias in the estimation of the design events, droughts and floods, when a strictly deterministic approach based on watershed simulation models is employed.

In the last decades, the number of available statistical tools, approaches, and procedures in several scientific fields has been increasing faster than before. The correct application of classical, updated, and new methods has always been fundamental for hydrological applications; moreover, for a single hydrological application, there are many potential statistical approaches available. As a consequence, in 2007 the "STAtistics in HYdrology" (STAHY) Working Group of the International Association of Hydrological Sciences (IAHS) was launched as a virtual common space aimed at synthesizing the enormous amount of information and number of resources present in the literature and beyond. The mission of this group was to coordinate, optimize and concentrate resources with the aims for statisticians to understand the hydrological applications, for hydrologists to understand and appropriately apply statistical tools and understand what is the correct or best approach, and for statistical hydrologists (who have peculiar expertise in the application and development of statistical methods for hydrological data) to easily be updated on recent advances in their research field. Thus, the working group contributed to advancing and promoting hydrological sciences worldwide, in line with the IAHS mission.

The STAHY Working Group successfully promoted and organized several initiatives toward the above directions. Contributions included several sessions at IAHS or IUGG General Assembly, annual STAHY Workshops, and several summer schools and short courses contributing to the development of new generations of statistical hydrologists; STAHY also collected recent scientific studies on statistical hydrology and awarded yearly the best ones (STAHY Best Paper Award). During the XXV IUGG General Assembly held in Melbourne Australia in 2011, the STAHY Working Group was transformed into the International Commission on Statistical Hydrology (ICSH-IAHS) to permanently give its contribution to the scientific community. Ever since, ICSH brought together people who wanted to actively collaborate by sharing knowledge, information, papers, data, and numerical routines. Up to the beginning of 2023, more than two hundred researchers from about 60 countries, from six continents, have joined the Commission.

The operational idea of ICSH was to focus the attention and to gather people around some main topics, emerging from the interest or explicitly suggested by the involved community. The most frequently discussed subjects in the ICSH-STAHY community from the very beginning are: (i) extreme value analysis, (ii) multivariate analysis, (iii) single or multiple time series analysis and modeling, and (iv) regionalization. Extreme events are important hydrological phenomena with serious societal consequences; their probability of being exceeded (or not) is determined in a univariate (i) or a multivariate (ii) framework, depending on the specific conditions. However, for general hydrological purposes, the statistical prediction of the magnitude and occurrence of extreme events may not be sufficient, and we need to model the temporal (iii) or spatial (iv) evolution of the entire hydrological process, considering its correlation structure. Obviously, these are only some of the topics of interest to the statistical hydrology community. Providing a comprehensive compendium of all or at least majority of the research areas related to or derived from those described here is far beyond the scope of this work. ■

Moreover, the ICSH-STAHY community actively contributes to many of the questions listed in the Unsolved Problems in Hydrology (UPH) community initiative (Blöschl et al., 2019), and, among them, the following ones are directly linked to ICSH-STAHY activities (even if almost all questions require the application of statistical tools):

- ✓ *Time variability and change*: 1. Is the hydrological cycle regionally accelerating/decelerating under climate and environmental change, and are there tipping points (irreversible changes)?
- ✓ *Space variability and scaling*: 6. What are the hydrologic laws at the catchment scale and how do they change with scale?
- ✓ *Variability of extremes*: 9. How do flood-rich and drought-rich periods arise, are they changing, and if so why?
- ✓ *Measurements and data*: 16. What is the relative value of traditional hydrological observations vs. soft data (qualitative observations from lay persons, data mining etc.), and under what conditions can we substitute space for time?
- ✓ *Modeling methods*: 20. How can we disentangle and reduce model structural/parameter/input uncertainty in hydrological prediction?
- ✓ *Interfaces with society*: 21. How can the (un)certainly in hydrological predictions be communicated to decision makers and the general public?

After 15 years since its establishment, the ICSH-STAHY community, represented by the authors of this work, aims to summarize the current state of the art in the aforementioned topics. Hence, the objective of this paper is to offer a critical review of the progress in the past 15 years, present standardized methods and procedures for various applications, and propose insights for the future advancement of statistical hydrology. Note, that the authors of this work are past and current officers of the ICSH-STAHY, as well as some members of the commission who were actively involved in the organization of recent initiatives. We are aware that the present work cannot be exhaustive, nor do we pretend to cover all relevant issues, of which there are many. However, we will mention, when relevant, some other topics or emerging areas of research that are more or less closely related to those discussed here (such as Bayesian methods, stochastic rainfall-runoff modeling, machine learning, etc.). Cross-cutting, emerging issues may be discussed in detail in a possible future development of this work (a series of manuscripts dedicated to specific issues).

The remainder of this paper is organized according to the four main topics mentioned above; the following sections are dedicated to one of the four research areas. For each of them, we present a brief state of the art, the milestones for driving practical applications, and the main open problems following the vision of the ICSH-STAHY community, as for the eye of the group of people authoring this work. Finally, each section is provided with some of the most popular Matlab® and R (R Core Team, 2020) packages for statistical analysis and modeling. Such packages can be accessed and downloaded either from The Comprehensive R Archive Network (CRAN), i.e. the official R-project package archive, or from other open-access repositories.

2. Extreme value analysis

When an extreme event occurs, key questions arise: is it going to happen again? How often? Can information from past events help with the prediction of the chance of future extremes? Answering these questions has led to significant advances in probability theory over the past century (see, e.g., Coles, 2001 and Koutsoyiannis, 2021). Indeed, human history has been shaped by and evolved also in response to natural disasters. In addition, anthropogenic induced change is expected to amplify the magnitude, frequency and effects of extreme events in the future.

The probability of an event (here, extreme flood, rainfall, drought) with a given magnitude can be broadly defined as the chance that the process of interest can exceed a certain high value (see Koutsoyiannis, 2021 and references therein). Contemporary frequency analysis in hydrology, as it is known today, started with Hazen in 1930 and was popularized by Gumbel (1958). The study on the concept of probability led to developing many distribution functions and answering several basic scientific and applied questions (Hald, 2005; Kelley, 1994). Hydrological frequency analysis broadly encompasses a set of statistical methods and techniques to link the magnitude of an extreme event to its frequency or chance of exceedance through a probability distribution function (see, e.g., Stedinger et al., 1993; El Adlouni et al., 2010; Camuffo et al., 2020), including distributions with an upper limit of the population, which corresponds to the concept of the Probable Maximum Precipitation (PMP) or the Probable Maximum Flood (PMF) (e.g. the recent Salas et al., 2020).

Extreme value analysis is well established in the literature and has a long history in hydrological theory and practice, as recalled above. Notwithstanding this, continued advances of hydrological knowledge incessantly open new questions, requiring innovative statistical tools to address them. In the following sections we briefly recall the most common approaches to extreme value analysis and focus on the latest open problems.

2.1. Common methodological approaches for extreme events frequency analysis

Typically, extreme value analysis involves the following five steps (e.g., Katz et al., 2022; Rao and Hamed, 2019):

- *Exploratory analysis.* Since hydrological data are generally asymmetric and the interest is in the distribution tail (where extremes occur), skewness and kurtosis are of particular interest in exploratory data analyses. For example, being a good indicator of a distribution's shape, the skewness is useful to guide the selection of a representative distribution. It is relevant to mention that it is generally more convenient to use the L-moments, L-skewness and L-kurtosis, instead of ordinary moments for this scope, as demonstrated in the seminal paper by Hosking (1990), as well as the comparative assessment in Vogel and Fennessey (1993). Another interesting approach is that recently proposed by Koutsoyiannis (2021) based on the so-called knowable moments. On the other hand, outliers can negatively affect the selection of an appropriate distribution (see, e.g., Lamontagne et al., 2016). For a summary of both parametric and nonparametric methods for exploratory

data analysis, the reader is referred to Helsel and Hirsch (1992) and Helsel et al. (2020).

- *Testing assumptions.* This step is important to ensure the validity of the subsequent steps. A number of homogeneity and stationarity testing methods are available in literature; the readers are referred to Naghettini (2017) for a review of the methods and, e.g., to Serinaldi et al. (2018), among others, for a discussion on trend tests (as briefly discussed in Section 4.3).
- *Modeling by probability distribution functions.* Fitting a probability distribution function to the observed data is perhaps the most developed step in hydrology and statistical theory literature; the remainder of this Section is indeed dedicated to hint at the most common modeling approaches.
- *Quantile and return period estimation.* The notions of quantile and return period (e.g., Fernández & Salas, 1999; Veneziano et al., 2007; Langousis et al., 2009; Volpi, 2019) for hydrological events are commonly used to describe the severity of extremes for a wide range of applications including hydraulic infrastructure design and risk assessment (e.g., Singh and Strupczewski, 2002; Vogel and Castellarin, 2017, among others).
- *Uncertainty estimation.* The evaluation of the uncertainty bounds (see, e.g., Coles, 2001), which depends on the length of the observed data and on modeling choices, is of paramount importance to understand and quantify the reliability for subsequent risk assessment and design. Note however, that additional uncertainty components with respect to uncertainty bounds are generally needed for risk-based decision making (see, e.g. Vogel and Castellarin, 2017).

The fundamental theory of distributions for hydrological frequency analysis of extreme events relies on the early work of Maurice Fréchet who showed in 1927 the asymptotic distributions of sampled extremes, which are typically selected as the annual maxima. After the Fisher's and Tippet's work in 1928, and Gnedenko's work in 1943, the Fréchet, Gumbel, and Weibull probability distributions emerge as limiting distributions of extremes (maxima sampled from fixed length sequences of independent random variables, referred also as block maxima). The combination of Fréchet, Gumbel, and Weibull resulted in the Generalized Extreme Value (GEV) distribution (Coles, 2001), which is characterized by the location, scale, and shape parameters; the latter determines not only the shape but also the tail behavior of the GEV distribution. As previously mentioned, in environmental applications, the most commonly applied approach is composed of maxima extracted from each 1-year long block of data, simply named Annual Maxima (AM). This assumption is a commonly accepted compromise in order to retain a reasonable number of observations free of seasonal and dependence biases.

Under a different framework aiming to enlarge the sample dimension, but with some analogies with the asymptotic properties of GEV, it can be proved that the Generalized Pareto (GP) is the expected asymptotic distribution of the rescaled exceedances above high enough thresholds, namely the Peaks-Over-Threshold (POT), regardless of the distribution of the underlying process (Coles, 2001). The more complex POT approach requires the proper definition of a high enough threshold to filter the data and calculate the frequency of the rescaled excesses (e.g., Deidda, 2010; Langousis et al., 2016a). The POT approach makes use of the

GP distribution, which is ruled by the threshold, scale parameter, and, similarly to GEV, shape parameter; again, the latter controls the tail behavior of the distribution.

A large number of studies apply the GEV and GP distributions to analyze extremes (see, e.g., Coles, 2001; Katz, 2013; El Adlouni et al., 2007; Tyralis et al., 2019; Emmanouil et al., 2020 among many others). In particular, Martins and Stedinger (2000) introduce the generalized maximum likelihood estimation for the GEV model; Hosking and Wallis (1987) provide seminal analyses and comparisons of both parameter estimation and quantile estimators for the GP model. Stedinger et al. (1993) (see also Madsen et al., 1997) summarize the various rigorous and classical studies, at that time, which led to the recommendation of POT over AM approaches when the arrival rate for the peaks over threshold is large enough (1.65 events/year for Poisson arrivals with exponential exceedances). In such instances POT analyses would yield more accurate estimates of extreme quantiles. O'Shea et al. (2023) argue that the POT series is better characterized using the 4-parameter Kappa (or, the combination of the GP and Binomial) for the estimation of rare to very-rare design extremes. Along with GEV and GP, many other distribution functions are used for frequency analysis of extremes, like Log-Pearson Type III (e.g., Griff and Stedinger, 2007), Burr Type (e.g. Zaghloul et al., 2020) or the Kappa distributions (see e.g. Hosking and Wallis, 1997 or Kjeldsen et al., 2017).

Frequency models can nevertheless differ not only in the choice of the shape of the distribution function, but also in the choice of the estimation method used to fit to model to the observed data. For a comprehensive review of the topic, including several examples of flood and rainfall extreme events, the readers are referred to Nerantzaki and Papalexiou (2022).

Noteworthy, there are no theoretical reasons that justify the a-priori assumption of a single specific distribution under non-asymptotic conditions; thus, the adoption of a specific model is generally motivated by its ability to robustly represent the available observed data (see e.g. Laio, 2004; El Adlouni et al., 2008; Laio et al., 2009 and Calenda et al., 2009 for possible examples of model selection criteria). Notice that even in the case of high accuracy in reproducing the observed data (which in fact hardly even happens), any adopted model provides only uncertain, and possibly biased estimates of higher extremes (e.g. in extrapolation) because the limited length of the available samples provides only poor information about rare events (Klemeš, 2000a, b). Special attention should be paid to the tail behavior (large or small extreme events) of the modeling distribution (El Adlouni et al., 2008; Kochanek et al., 2020; see also Merz et al., 2022 and references therein). In addition to parametric models, which can be easily applied in extrapolation, a wide range of distribution-free, non-parametric, semi-parametric or kernel-based methods have also been developed in the literature (see, e.g., Lall, 1995, Rao and Hamed, 2019, Banfi et al., 2022).

Finally, Table 1 reports a selected list of packages already available for extreme events frequency analysis, mainly R packages available by R Core Team (2020), yet not only.

Table 1 – Packages for extreme events frequency analysis and modeling (see also the CRAN Task View: Hydrological Data and Modeling <https://cran.r-project.org/web/views/Hydrology.html>).

Name	Brief description	Repo.	Link	Authors
ProNEVA	Process-informed Nonstationary Extreme Value Analysis	UCL.edu	https://amir.eng.uci.edu/software.php	Ragno et al. (2019)
NEVA	Nonstationary Extreme Value Analysis	UCL.edu	https://amir.eng.uci.edu/software.php	Cheng et al. (2014)
MEV	Modelling of Extreme Values	CRAN	https://cran.r-project.org/web/packages/mev/index.html	Leo Belzile et al.
UKFL	UK Flood Estimation	CRAN	https://CRAN.R-project.org/package=UKFE	Hammond A.
PeakFQ	Flood Frequency Analysis Based on US Bulletin 17C	USGS	http://water.usgs.gov/software/PeakFQ/	Veilleux, A.G., Cohn, T.A., Flynn, K.M., Mason, R.R., Jr., and Hummel, P.R. (2014)
Afins	Unbounded and bounded distributions with non-systematic information	UPV	http://luvia.dihma.upv.es/EN/software/software.html	Botero and Francés (2010)
GAMLSS	Generalized Additive Models for Location, Scale and Shape	CRAN	https://cran.r-project.org/web/packages/gamlss/index.html	Rigby R.A., Stasinopoulos D.M. (2005)
extRemes	General functions for performing extreme value analysis.	CRAN	https://CRAN.R-project.org/package=extRemes	E. Gilleland and R. W. Katz (2016)
lmom	Functions related to L-moments: computation of L-moments and trimmed L-moments of distributions and data samples; parameter estimation.	CRAN	https://CRAN.R-project.org/package=lmom	J.R.M. Hosking
LMoFit	Advanced L-Moment Fitting of Distributions	CRAN	https://cran.r-project.org/web/packages/LMoFit/index.html	M. Zaghloul, S.M. Papalexiou, A. Elshorbagy
LMOMCO	L-Moments, Censored L-Moments, Trimmed L-Moments, LComoments, and Many Distributions	CRAN	https://cran.rproject.org/web/packages/lmomco/lmomco.pdf	Asquith (2011)
USGSR/smwrStats	R functions to support statistical methods in water resources	CRAN	https://rdr.io/github/USGSR/	Lorenz (2015)

		smwrStats/	
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2.2. Incorporating additional information: historical events, seasonality and time-dependence of the underlying process

Besides the two classical approaches for considering extreme events in hydrology mentioned in the previous section (Section 2.1), namely AM and POT, several extensions exist that aim at increasing the information incorporated in the samples. Indeed, both these classical approaches lead to formulations neglecting a significant proportion of the observations, discarding the information contained in the bulk of the parent distribution along with most of the observations. The bulk of the distribution may add information on the extreme events assuming that they pertain to the same process (as in GEV and POT derivations). In addition, extreme events may be differentiated by the season they occur in (see, e.g., Baratti et al., 2012, Strupczewski et al., 2012 and Kochanek et al. 2012 for applications in flood frequency analysis and Mascaro, 2018 for extreme rainfall events). Another development is the use of flood-type-specific samples that are considered in a joint mixture model (as in Hirschboek, 1987; Fischer, 2018; Fischer and Schumann, 2021). These sub-samples are assumed to be identically distributed and more homogeneous than the annual or partial duration series since the events can be assumed to have a common genesis.

In general, any additional information about the process of interest notably improves return period estimates. In the last decades, several researchers have evaluated the possibility of extending the data to past, non-systematically recorded events, leading to a significant increase in the length of the available datasets, with benefits toward the frequency analysis of hydrological extremes. This non-systematic data can have two different sources: historical and palaeoflood information. The use of historical information in the estimation of flood quantiles was first described by Benson (1950) and Leese (1973). Techniques for obtaining information from palaeofloods were first introduced by Costa (1978) and Kochel and Baker (1982).

Stedinger and Cohn (1986), Cohn and Stedinger (1987) and Frances et al. (1994) systematized the use of these types of information and demonstrated their enormous advantage in reducing the uncertainty of the estimated quantiles. This has led to the development of historical hydrology (see, e.g., Benito et al., 2004; Macharo et al., 2015), that involves the use of historical-archival methods, of hydrological modeling and stochastic frequency analysis (from Stedinger and Cohn, 1986 to, e.g., Francés et al, 1994; Reis and Stedinger, 2005; Naulet et al., 2005; Calenda et al., 2009; Botero and Francés, 2010; Blöschl et al., 2020; Ostrowski et al., 2023; Saint Ciriq et al., 2022, and many more).

A promising technique for improving the reliability of high return period quantiles is based on a better understanding of the emergence of extreme events from the bulk of the distributions, as suggested by Marani and Ignaccolo (2015) and Zorzetto et al. (2016) or differently by Volpi et al. (2019). This might require relaxing the asymptotic hypothesis or the underlying, common hypothesis of independence of sample data used for inference and projection. The extension of frequency analysis

and return period estimate for time-dependent data was recently discussed by Volpi et al. (2015), Serinaldi and Kilsby (2016, 2018) and Serinaldi and Lombardo (2020) and references therein.

In particular, the Metastatistical Extreme Value (MEV) approach by Marani and Ignaccolo (2015) relies on the assumption that the extreme events are block maxima among a finite and stochastically variable number of *ordinary events* from an underlying and possibly time-varying parent distribution. Then, the MEV approach relaxes the limiting assumptions of the classical extreme value theory by considering as random variables the parameters defining the number of ordinary events and the probability distribution of event magnitudes. This allows the use of the entire observational set to infer the distribution of extremes and significantly reduce the estimation uncertainty (see, e.g., Marra et al., 2023).

Another way to increase the acquired information from samples of limited length is to apply statistical models that simultaneously incorporate information from a wide range of spatiotemporal scales. Under this setting, during the last four decades, scaling representations of hydrological processes have attracted much attention, with particular emphasis on extreme estimation under asymptotic (e.g., Veneziano and Langousis, 2005a and the review in Veneziano et al., 2006) and pre-asymptotic (e.g., Langousis et al., 2013; Grimaldi et al., 2022; Emmanouil et al., 2020, 2022, 2023) conditions.

Stochastic models (see Section 4) have been also used to extract information from samples of limited lengths. The idea is to calibrate a model that is capable of generating replicas of observed time series, therefore obtaining multiple realizations of the considered stochastic process. These models were pioneered by the contributions of Andrey Markov (1856 – 1922) and then widely used by hydrologists since the second half of the twentieth century (see, for instance, Thomas & Fiering, 1962). The use of stochastic models for inferring extreme values has been problematic for the complexity associated with the simulation of the distribution tails of non-Gaussian processes. However, recent scientific contributions opened promising doors for resolving such limitation (Papalexiou and Serinaldi, 2020; see also Section 4). In particular, stochastic streamflow models are needed for risk-based hydrologic management methods because such models can generate the ensembles needed for such planning exercises. Vogel (2017, section 2) gives a historical perspective on the application of such models in hydrology and provides arguments for the need for a new generation of stochastic watershed models for generating such streamflow ensembles particularly when purely statistical/machine learning models are inadequate to the task, because they may not be able to incorporate explicitly, the impact of anthropogenic influences.

2.3. Changing Extremes: Stationarity versus non-stationarity

A fundamental assumption for the extreme value analysis is that the random variable of interest should be independently and identically distributed (i.i.d.). Note that, as discussed in the previous section, while the independence assumption can be relaxed, the identical distribution implies that the statistical properties of the historical data, i.e., the relationship between the magnitudes and return periods based on frequency analysis of data, should be invariant and thus, representative

of future events. The longer the observed data, the higher the chance is that historical extremes represent a reasonable sample for what is expected to occur in the future (Klemeš, 2000a, b). However, if the statistics of future extremes are expected to significantly vary from the past, return periods and occurrence probabilities estimated based on historical observations may not be representative of the future scenarios.

While hydrologic extremes are expected to show significant natural variability, anthropogenic activities including greenhouse gas emissions and land use – land cover changes are expected to alter the magnitude and severity of extreme events (e.g., Milly et al., 2008, 2015; Chiang et al., 2021). Over the past two decades, numerous studies have pointed to more intense and frequent extreme rainfall events (e.g., Alexander et al., 2006; Ragno et al., 2018; Fischer and Knutti, 2016; Mallakpour and Villarini, 2017; Westra et al., 2014; Farris et al., 2021; Emmanouil et al., 2022, 2023), changes in the mean and variability of river flows (e.g., Hodgkins et al., 2017; Blöschl et al., 2017, 2019), as well as sea level rise with implications for severe coastal flooding (e.g., Vermeer and Rahmstorf, 2009; Wahl et al., 2015). As for floods, changes in both hydroclimatology and land use showed a strong impact; as an example, in a comparative national assessment on the magnification of floods, Vogel et al. (2011) found that urbanization impacts were at that time more severe (led to higher magnification factors) and obvious (common) than impacts due to climate change.

Current operational procedures, risk assessment methods and design guidelines are based on the so-called “stationarity” assumption, which implies invariant properties of hydrologic extremes from historical records. In other words, a stationary approach assumes that the properties of the underlying stochastic model (i.e. all finite-dimensional distributions, including the statistics of extremes) do not change significantly relative to time or another physically based variable. Indeed, change in the observed data does not necessarily imply a nonstationary underlying process; and stationarity is also related to ergodicity, which in turn is a prerequisite to making inference from data (Cohn and Lins, 2005; Koutsoyiannis and Montanari, 2015). Furthermore, a nonstationary framework cannot be generally inferred from the observed data alone, i.e. without a wide a priori discussion about the physical reasons and the expected change (Koutsoyiannis, 2016; Luke et al., 2017; Serinaldi and Kilsby, 2015).

A non-stationary assumption corresponds to the changing properties of the hydrologic extremes over time in response to a physically-based process. It is generally suggested to use as covariates for change the forcings of that change through climate, land use and/or reservoir indices instead of time (Villarini et al., 2009; López & Francés, 2013; Ragno et al., 2019; Katz, 2013). Following a popular publication on the “death of the stationarity assumption” due to significant human activities (Milly et al., 2008), a lively debate emerged in the literature on the validity of the stationary and non-stationary approaches (Koutsoyiannis and Montanari, 2015; Luke et al., 2017; Ragno et al., 2019; Milly et al., 2015; Matalas, 2012; Lins and Cohn, 2011; Serinaldi and Kilsby, 2015). Some key questions are:

- Is the commonly used stationary method (or alternative versions still based on the same fundamental assumptions) sufficient for analysis of future extremes?

- Do we need a new paradigm for analysis of changing extremes?
- How can we confidently decide whether the statistics of extremes have changed or not?
- Is non-stationarity a property of the natural system (including human interactions) or simply a property of a numerical model?
- Do we have sufficient observations to test and develop nonstationary models for analysis of hydrologic extremes?
- What is the predictability power of a nonstationary framework?

This is not an exhaustive list of all the questions, on the contrary, the list of relevant questions and concerns is long and still growing (e.g., Koutsoyiannis, 2020). The purpose of this section is not to take a position as to which approach is more justified in a changing environment. Instead, we highlight that this area of research still deserves more in-depth exploration, and model development. Regarding the methods for change analysis of the observed data, we refer the reader to Section 4.3.

The non-stationary assumption is typically implemented through changing one or more parameters of the corresponding extreme value distribution with respect to an underlying physical process driving change. Time is often used as a surrogate for other drivers, but the use of appropriate physically based covariates instead of time alone should be preferred, as previously mentioned. In the case of GEV for example, one can allow the location, scale and/or shape parameters to vary as a (e.g. linear) function of one or more covariates. The shape parameter is the most sensitive one and it is difficult to estimate accurately when the availability of the observations is limited (see e.g. Coles, 2001; El Adlouni et al., 2007; Papalexiou and Koutsoyiannis, 2013; Strupczewski, et al. 2016; Deidda et al., 2021). Ouarda and Charron (2019) showed that the shape parameter can evolve as a function of time and low-frequency climate oscillation indices and that its evolution affects considerably the estimates of extreme events. The appropriateness of the nonlinear function and its validity in the future are among the major sources of uncertainty (Koutsoyiannis, 2020). As pointed out by Prosdocimi and Kjeldsen (2021), combining time-varying parameters can lead to a counter intuitive behaviour in the extreme quantiles of interest for hydrological design. Hence, a wide discussion on what types of changes can be a-priori expected under different conditions is necessary to clarify what parameter model structures are more apt to capture the expected changes (see, e.g., Sharma et al., 2018 and Hecht and Vogel, 2020).

Regardless of the choice of the parameter model structure, the outcome will be a distribution function that changes over time due to varying parameters. Ouarda et al. (2020) presented a comparison of the uncertainties in stationary and non-stationary extreme rainfall models and formulated words of caution about the use of nonstationary models with relatively small size data samples. In recent studies, Prosdocimi et al. (2015) and Bertola et al. (2019) among many others showed how physical processes can be integrated into regional and at-site nonstationary analysis of extremes such as changes in flooding as a function of land use change, increases in temperature as a function of CO₂ concentration in the atmosphere, and

changes in rainfall and snowmelt patterns providing a deterministic justification for non-stationary statistics.

Despite progress in this area (summarized broadly in Slater et al. 2021b), in most places around the world, official codes and guidelines do not consider changing extremes. For the first time, the American Society of Civil Engineers (ASCE Manual of Practice 140, 2018) published a manual of practice including a guideline for considering the observed and projected changes in extreme precipitation events assessment based on Ragno et al. (2018) for design and risk (ASCE). To avoid assumptions associated with changing trends in the future (e.g., Koutsoyiannis, 2020), the guideline recommends using a wide range of future projections to update historical precipitation Intensity-Duration-Frequency (IDF) curves. This approach, presented here as an example, allows for quantifying the changes in the frequency of past events (or return period of a historical event), when historical and projected IDF curves are available. Figure 1 (left) displays a historical IDF curve (blue line) and the projected IDF curves derived from a wide range of climate model simulations (red ensemble) in San Francisco, California (USA). Given that this method is based on a wide range of models, one can derive the 5th and 95th percentiles as a measure of uncertainty (Figure 1). Needless to mention that when comparing the expected value from future projections and historical observations, the most conservative one should be considered for design and risk assessment. Given the uncertainties associated with future projections, the difference between future projections and historical observations can be very large.

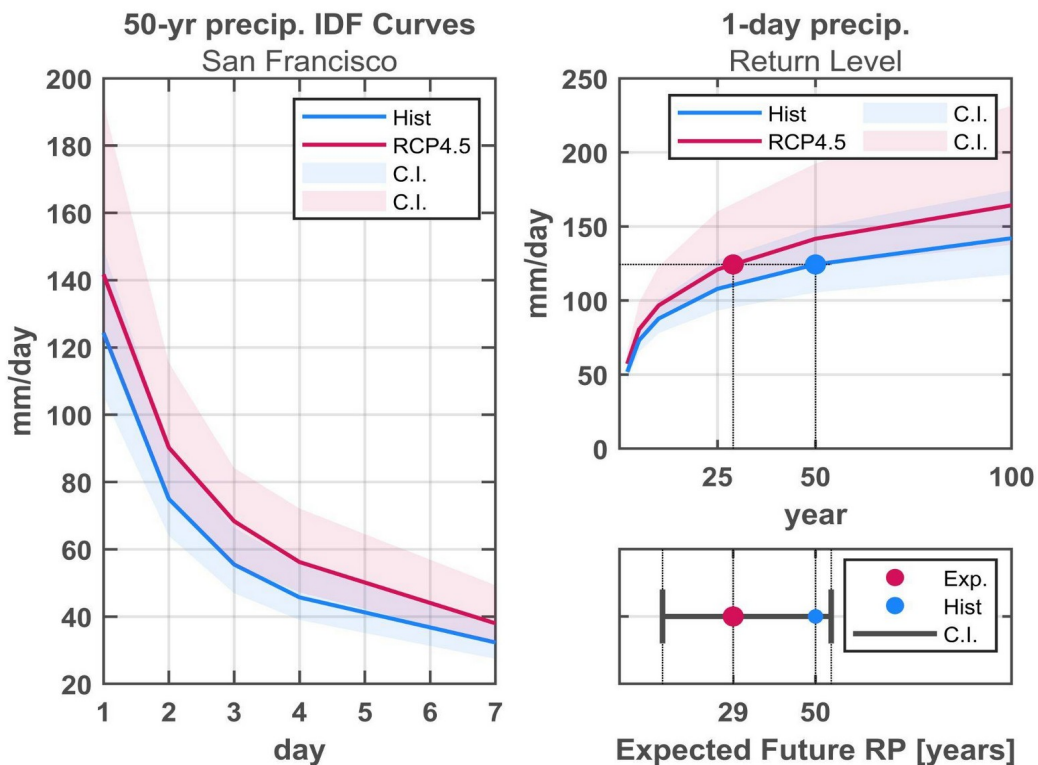


Figure 1 – Left panel shows the IDF curves together with their confidence intervals (C.I.) from multi-model climate simulations of the future (red) relative to the IDF curves from historical observations (blue). The right panels illustrate the changes in the historical 50-year event.

Ouarda et al. (2019) proposed an IDF model in which the parameters depend on time and low-frequency climate oscillation indices and are estimated with the maximum composite likelihood method. Results indicated that the non-stationary

IDF framework provides a better fit to the data and leads to more robust estimates. Other well-known approaches dealing with the assumption of non-stationarity are the effective return level (Katz et al., 2002) and the expected waiting time (Salas and Obeysekera, 2014). The effective return level (or effective design value), proposed by Katz et al. (2002) is the quantile expressed as a function of a given covariate (i.e., time or physical). The expected waiting time, proposed by Salas and Obeysekera (2014), is the non-stationary return period of an event of interest derived as the expectation of a geometric distribution in which the probability of the first occurrence of the event of interest changes over time. Compared to other approaches, the expected waiting time is consistent with the definition of the return period in the stationary case.

Summarizing, the extrapolation of non-stationary behaviors to the future should be done with caution, and only if the future can be predicted by using additional prior physical knowledge of the process (e.g., Prosdociimi et al., 2015; Serago and Vogel, 2018; Bertola et al., 2019; Ouarda et al., 2020). The additional information justifies the reduction of uncertainty that might result from explaining part of the variability in deterministic terms (Koutsoyiannis and Montanari, 2015); otherwise, the effect would be that of introducing an additional source of uncertainty (Serinaldi and Kilsby, 2015). Detailed discussion on the stationarity issue can be found in Salas et al. (2018) and Vogel and Castellarin (2017). Depending on the available information, different approaches can be applied, stationary and non-stationary; in any case, results should be evaluated in terms of both accuracy and uncertainty. In Table 1 some packages for non-stationary frequency analysis are listed.

3. Multivariate frequency analysis

Univariate frequency analysis deals with only one variable or feature of a hydrological phenomenon (e.g., drought intensity or flood peak); however, hydrological events are often characterized by several features that might be interrelated, e.g., flood peak, volume and duration, drought severity and duration, storm precipitation, intensity and duration, fluvial and oceanic floods, heatwave duration and severity, extreme discharge in two (or more) rivers in the same catchment. A multivariate frequency analysis framework may involve jointly modeling two or more features of the extreme events (e.g., flood volume and peak), or multi-site analysis of extremes across space (e.g., flood peaks at several locations) or compound extreme events.

In the last two decades, multivariate frequency analysis has attracted increasing attention focusing on the joint treatment of different variables mainly using multivariate distributions (e.g., Yue et al., 1999) or copulas (e.g., Salvadori and De Michele, 2004; Chebana, 2022). In recent years, several studies, review papers and books discussed multivariate hydrological frequency analysis methodologies and applications (e.g., Favre et al., 2004; Zhang and Singh, 2006; Salvadori et al., 2007; Genest and Favre, 2007; Ashkar and Aucoin, 2011; Joe, 2014; Genest and Chebana, 2017; Zhang and Singh, 2019). Some previous studies highlight the limitations of the univariate framework and justify the adoption of an alternative multivariate framework in hydrological applications (see Salvadori and De Michele, 2004 and Kao and Govindaraju, 2007). This is particularly important for compound and

cascading hazards and other interrelated hydrologic extremes (e.g., Sadegh et al., 2018; AghaKouchak et al., 2020; Zscheischler et al., 2018).

The application of multivariate models in hydrology is not a new topic and numerous previous studies have employed multivariate Normal, Gamma and Exponential distribution functions, among others, to understand and model the relationship among different variables. However, multivariate distributions have several limitations. For example, they require the marginal distributions of associated random variables to be within the same class, leading to only a limited number of the common distributions extendable to a multivariate setting (e.g., Hao and Singh, 2016). To overcome such drawback, in some cases a multivariate distribution can be derived analytically based on the nature of the process under investigation, e.g. for the case of droughts (Cancelliere and Salas, 2010). An alternative and more general approach employs copula functions for hydrological frequency analysis to avoid the drawbacks of classical multivariate models (Nelsen, 2006). In fact, copulas can model the dependence structure independently of the marginal distributions, making it possible to build multivariate distributions with different margins.

The literature on copulas and their applications to hydrology is already substantial (for recent reviews see Hao and Singh, 2016; Genest and Chebana, 2017 and Zhang and Singh, 2019). Copulas are increasingly used in multivariate analysis such as for precipitations (e.g., Grimaldi and Serinaldi, 2006a; Sharma and Mujumdar, 2019; Xu et al., 2020), droughts (e.g., Serinaldi et al., 2009; Vazifekhah et al., 2019), floods (e.g., Grimaldi and Serinaldi, 2006b; Durocher et al., 2016), river discharge estimate (e.g., Ragno et al 2022), reservoir routing for dam design and safety assessment (Requena et al., 2013; Volpi and Fiori, 2014), heatwaves (Mazdiyassni et al., 2019), storms and extremes (e.g., Corbella and Stretch, 2013; Han et al., 2020) and multi-index drought assessment (e.g., Hao and AghaKouchak, 2014). Copulas are also used for the joint modeling of extreme river temperature and low flow conditions which can be harmful to aquatic life (Latif et al., 2023). They are also useful for multi-site analysis (e.g., Serinaldi, 2009).

In this Section, we refer to the common methodological approaches used for multivariate frequency analysis based on copula functions. The advantage of considering multivariate hydrological frequency analysis also involve some challenges and issues (e.g., variable selection, choice of dimension, event selection, and dealing with more parameters), as it may require different definitions of a given statistical concept (e.g., return period) depending on the application, and often needs large data series compared to univariate analysis, as described in the last part of this Section. Typically, multivariate frequency analysis involves the same four steps already described for the univariate setting in Section 2. Karahacane et al. (2020) is one of the rare papers dealing with most of these aspects simultaneously. We recall here some issues that are specific to multivariate analysis.

- *Exploratory analysis.* In a multivariate setting, Chebana and Ouarda (2011a) investigated this step and offered guidelines on how to explore the data prior to modeling. In addition, at this step, missing data and ties (if applicable) should also be treated (e.g., Ben Aissia et al., 2017), as well as sample dimension. There is no general recommendation concerning the minimum

number of pairs or triplets for multivariate analysis, however, it is reasonable to avoid bivariate analysis with just 30-40 pairs.

- *Testing assumptions.* A number of multivariate homogeneity and stationarity testing methods are available in the literature. Specifically, multivariate trend tests can be found in Chebana et al. (2013) whereas multivariate shift testing (homogeneity) is discussed in Chebana et al. (2017) and Salvadori et al. (2018). A pivotal requirement, often not verified, is the serial independence condition that can easily be preliminarily checked on the autocorrelation structure of each sample (Chebana et al., 2013, Tootoonchi et al., 2020).
- *Modeling by probability distribution functions.* A large number of studies have focused on copula fitting and parameter estimation for a wide range of hydrologic applications (e.g., Zhang and Singh, 2006; Salvadori and De Michele, 2007; Kao and Govindaraju, 2008; Requena et al., 2016). Given their importance, copulas are described in more detail in the following sections.
- *Multivariate quantile and return period analysis.* For multivariate return period analyses, one can refer, for instance, to Salvadori et al. (2007), Gräler et al. (2013), Serinaldi (2015), Salvadori et al. (2016), whereas multivariate quantiles are investigated in Chebana and Ouarda (2011b). In summary, the multivariate return period is different from the univariate one, because in the multivariate setting the bijective relationship between return period and return level (or quantile) does not hold anymore. Volpi and Fiori (2012 and 2014) treated design event selection, as a practical aspect, in the multivariate return period and quantile framework for risk assessment or infrastructure design. Note that the return period of structural failure does not necessarily match that of the hydrological load in a multivariate setting (see also Cipollini et al., 2021).
- *Uncertainty estimation.* As discussed below for the case of copula-based multivariate frequency analysis, uncertainty estimation in a multivariate setting still requires additional developments and implementations of practical applications (see, e.g., Serinaldi, 2013).

3.1. Copula functions

Copulas are an ingredient for constructing multivariate distributions with margins from different families. Basically, a copula is a multivariate distribution function with uniform margins. An attractive advantage of copulas is that the dependence between variables can be modeled separately from their marginal distributions (e.g., Joe, 2014; Nelsen, 2006). Another interesting feature is that multivariate analysis based on copula can use all the common tools of univariate analysis.

In the following, we consider the bivariate case for simplicity even though the majority of the material presented below is available in higher dimensions. According to Sklar's theorem (Sklar, 1959), the joint probability distribution of two random variables can be decomposed into two marginals as well as a copula to describe the dependence structure between the variables. The copula is unique when the marginals are continuous, which is a common assumption in hydrology. The copula captures the dependence structure between variables, and provides

more information beyond descriptive dependence measures (e.g., Kendall's tau and Spearman's rho, defined below).

The Archimedean, Meta-elliptical, and Extreme Value copula families are of particular interest in statistics as well as in hydrology. Lists and properties of different copulas can be found, for instance, in Salvadori et al. (2007), Nelsen (2006), Joe (2014), and Zhang and Singh (2019); we recall in the following the main properties of some of the copulas.

- *Archimedean copulas.* This class is widely used in hydrology because: i) they are easy to construct and the parameter estimation is straightforward; ii) this family includes a diverse set of copulas with different properties applicable to a wide range of data; and iii) mathematically, they are elegant to treat. Archimedean copulas are based on a generator function, including Ali-Mikhail-Haq, Clayton, Frank, Joe and Gumbel-Hougaard, among others. Multi-parameter Archimedean copulas are also available and can be found in Joe (2014) in the general statistical context and, e.g., in Sadegh et al. (2018) for hydrological applications. In hydrology and in multivariate analysis, the Archimedean copula family is probably the most widely used among different options (see among many others, Kao and Govindaraju, 2007; Chebana and Ouada, 2011b; Liu et al., 2020). Several studies have explored using Archimedean copulas at higher dimensions such as three and four (e.g., Grimaldi and Serinaldi, 2006a; Zhang and Singh, 2007a, b); however, care should be taken in high dimensional applications as the performance of most Archimedean copulas reduces as the dimension increases (Joe, 2014). Finally, asymmetric (also called nested) versions of Archimedean copulas have been introduced and used in hydrology to model joint distributions of more than two random variables (e.g., Grimaldi and Serinaldi, 2006b; Ma et al., 2013).
- *Extreme-value (EV) copulas.* This class is particularly attractive for block maxima data (i.e., annual maximum series of daily flows) – see for example, Salvadori and De Michele (2011). EV copulas are defined on the basis of a dependence function, known as the Pickands dependence function, which plays a similar role for EV copulas as generators for Archimedean copulas. Among the well-known copulas in this class, one can find Galambos, Hüsler-Resiss, Tawn and Gumbel (which is also Archimedean). EV copulas have been used in numerous multivariate hydrological studies, such as investigating floods and droughts (e.g., Zhang and Singh, 2006; Salvadori and De Michele, 2011; Sharma and Mujumdar, 2019). See Genest and Chebana (2017) for the mathematical expressions in d -dimensions and Genest and Nešlehová (2012b) for a review and more technical details.
- *Meta-elliptical copulas.* Meta-elliptical copulas are derived from elliptical distributions (e.g., Kotz and Nadarajah, 2000). Convenience and flexibility are the key characteristics of meta-elliptical copulas (Genest et al., 2007). The normal and multivariate Student t copulas are among the most used copulas of this class in the hydrology literature including droughts, floods, and extreme rainfall analysis (e.g., Zhang and Singh, 2019 - Table 7.1; Salvadori et al., 2007; Ma et al., 2013; Tosunoglu and Singh, 2018). For more details

and mathematical formulation, the interested reader is referred, for instance, to Genest and Chebana (2017) and Chebana (2022).

- *Other classes of copulas.* Even though the above classes of copulas are the most developed and used, a number of other classes are also available, such as the Farlie-Gumbel-Morgenstern (FGM), Plackett, entropy, Vine copula, flipped copula and others. Even though the FGM copula imposes moderate dependence, it is attractive because of its simplicity and hence, has been used in a number of hydrological studies (e.g., Papaioannou et al., 2016). The Plackett copula has also been used in hydrology in a number of studies such as Kao and Govindaraju (2008) and Papaioannou et al. (2016). Despite their significant potential, only limited hydrological applications have explored entropy copulas (e.g., Piantadosi et al., 2012). Given their flexibility, especially for high dimensional analysis, Vine copulas have recently received a great deal of attention in hydrology (e.g., Tosunoglu and Singh, 2018). The nonparametric copula framework is also receiving increasing attention in the field of hydrology because of its flexibility and its capacity to adapt to any mutual dependence structure (e.g. Latif et al., 2024). Finally, it is worth mentioning the framework for the construction of multivariate non-Gaussian distributions presented by Bárdossy (2023); the framework can represent monotonic dependence but also dependencies with changing character, for example negative dependence for small values and positive dependence for high values.

3.2. Dependence measures, correlation and tail dependence

Dependence measure coefficients that summarize the degree of association between two or more variables are widely used in hydrology. The Pearson's ρ_P , Kendall's τ_K and Spearman's ρ_S correlation coefficients, and the Upper-Lower tail dependence coefficients are the most used measures of dependence (e.g., Joe, 2014; Nelsen 2006). The Pearson correlation coefficient has several limitations, including linearity, and is not margin-free (Barber et al., 2020).

The population versions of τ_K and ρ_S can be obtained in terms of copula as explicit relations or through numerical approximations (for many Archimedean copulas see Zhang and Singh, 2019). These relations are the basis of the method of moments for copula parameter estimation. Considering these coefficients is useful in preliminary copula selection as the values of τ_K and ρ_S for some copula families are restricted.

Tail dependence coefficients (upper λ_u^c and lower λ_l^c) can be used to detect and quantify the presence of extremal dependence. Tail dependence plays an important role in analyzing dependent hydrologic extremes (e.g., Poulin et al., 2007; Lee et al., 2013; Genest and Chebana, 2017). Expressions of λ_u^c and λ_l^c can be obtained with respect to the parameters or generators of some common copulas (e.g., Salvadori et al., 2007 and Joe, 2014). Important differences between copulas can be revealed by investigating their λ_u^c and λ_l^c coefficients. As an example, the Normal copula exhibits no tail dependence (null coefficients), whereas the Student-t copula offers substantially strong tail dependence (strictly positive coefficients).

Hence, the former can potentially lead to an underestimation of joint extremes when considering multiple related hazards (e.g., McNeil et al., 2015). Estimators for tail dependence coefficients, developed by Capéraà et al. (1997) and Frahm (2006), have been already used in the hydrology literature (e.g., Requena et al., 2013). Lekina et al. (2015) considered different tail dependence measures in hydrology and recommended considering more than one tail dependence measure, primarily because the upper tail dependence measure could fail to discriminate between the degrees of relative strength of dependence in asymptotically independent variables.

3.3. Multivariate inference with copulas

Selecting the most appropriate multivariate distribution for a given data set is crucial. According to Sklar (1959), the selection of the joint distribution is equivalent to the selection of a copula and the margins. In this section, we focus on the key steps to select the copula since the process of choosing the margins aligns with the approach used in the univariate framework (e.g., Laio et al., 2009).

After transforming the margins into uniform, different copula models should be considered to find the best one for characterizing the dependence structure of the variables in hand. When selecting the appropriate copula, several issues need to be considered including the type of dependence structure, parameter estimation method, goodness-of-fit tests, selection criteria, and tail dependence (e.g., Genest and Chebana, 2017).

- *Preliminary step.* A preliminary exploratory step can guide copula selection by, for instance, excluding some copulas that cannot describe the empirical dependence. This evaluation can start computing dependence measures (τ_K , ρ_S , and λ^c) to select potentially applicable copula candidates since not all copulas support all correlation coefficient and tail dependence values (e.g., Michiels and Schepper, 2008; Poulin et al., 2007). Graphical tools (e.g., rank plots, rankit and K-plot, empirical copulas) can also provide interesting information about the dependence structure and hence help to select potential copula candidates through some characteristics such as departures from bivariate normality, presence of heavy tails, symmetry or asymmetry, strength of dependence, and extreme-value.
- *Parameter estimation.* Several methods of copula parameter estimation are available in the literature including the Inference Function of Margins (IFM), Maximum Pseudo Likelihood (MPL), Method of Moments (MM), and Bayesian parameter estimation (see, e.g., Hofert et al., 2012 and Sadegh et al., 2018; for additional details the reader is referred to Genest and Chebana, 2017). In the IFM method, the joint likelihood function is maximized in two steps (Joe, 2014): first, the marginal log-likelihood is maximized leading to an estimate of the margin parameters; then, the latter is plugged into the joint likelihood function to obtain a log-likelihood function for the copula parameter. The obtained copula parameter estimator is consistent and asymptotically normal. By maximizing the pseudo-likelihood (MPL), the obtained estimator of the copula parameter is not affected by marginal misspecifications. The MPL estimator is consistent and asymptotically normal under reasonable

conditions; however, it is generally less efficient than the full maximum likelihood estimator when the margins are properly specified, except at independence. Overall, the MPL method is shown to have good performance, is considered as the best option, and is widely applied to one-parameter and multi-parameter copulas (e.g., Kim et al., 2007; Kojadinovic and Yan, 2010). As indicated above, for some copulas, their parameter can be expressed as a function of Kendall's τ_K or Spearman's ρ_s ; hence, a direct MM estimate of the copula parameter is obtained by estimating τ_K or ρ_s , respectively. Given their simplicity, MM estimators can provide reliable starting values for numerical (pseudo) likelihood maximization. Compared to IFM- or MPL-based estimators, the MM-based estimators are generally less efficient and may need to be adjusted to remain within the possibly limited range of the parameters. Further, moment-based methods have limitations in characterizing the underlying uncertainties; for this reason, using Bayesian methods and global optimization approaches have gained attention for inferring copula parameters (Sadegh et al., 2018; Kwon and Lall, 2016). For example, Sadegh et al. (2017) introduced a hybrid Markov Chain Monte Carlo (MCMC) simulation within a Bayesian framework for estimating a wide range of copula families with one to three parameters. The MCMC simulations estimate the posterior distribution of each copula parameter values, which can be translated into uncertainty ranges for return periods and probability isolines.

- *Copula goodness-of-fit testing.* It is important and necessary to proceed with a formal goodness-of-fit testing of the preliminarily selected copula to ensure the model is representative. A number of goodness-of-fit tests for copulas have been proposed in the statistical literature (e.g., Zhang and Singh, 2019). After a comprehensive assessment based on large simulations by Genest et al. (2009) and Berg (2009), it is deemed that goodness-of-fit testing based on empirical copula performs particularly well. Hence, a widely used goodness-of-fit test is based on the deviation between the empirical and the theoretical copula where the copula parameter is estimated on n pseudo-observations (such as the MPL estimator). One of the most powerful, easy to apply, general and widely used goodness-of-fit tests is based on the Cramér-von Mises statistics (Genest and Nešlehová, 2012b).

Tests based on the Rosenblatt transformation or on nonparametric estimates of the copula density are among other goodness-of-fit tests available in the literature. These tests are general and conceptually valid for any copula. However, specific tests have been developed for specific dependence structures such as for Clayton copula, Gaussian copula, and even extreme-value and Archimedean copula classes (see e.g., Genest and Nešlehová, 2012b). Goodness-of-fit tests for a specific but large class of copulas are also emerging, for instance, the class of bivariate exchangeable copulas, spatial copulas and multi-parameter copulas. Given the importance of the Archimedean and extreme-value copula classes in hydrological and other applications, specific goodness-of-fit tests are available (see Genest and Nešlehová, 2012b or Genest and Chebana, 2017 and the references therein). The p -value approximation of all the above tests (excluding Bayesian-based methods) can be obtained by a parametric bootstrap framework (Genest and

Rémillard, 2008). However, computational costs can be high, especially when the sample size increases. Based on the multiplier central limit theorems, Kojadinovic et al. (2011) proposed a faster and more efficient procedure for large samples, yet, for such samples, it is hard to find a copula that passes the above goodness-of-fit tests.

- *Selection criteria for copula.* For a given data set, the goodness-of-fit test can lead to more than one accepted model. Then, several selection criteria can be used to help identify the most appropriate copula from the set of acceptable ones (e.g., Zhang and Singh, 2006; Requena et al., 2013; Genest and Chebana, 2017). Among the popular criteria are the Akaike Information Criterion (AIC) and Bayesian Information Criterion (BIC). The general AIC formulation is based on the maximum likelihood (ML) of a given model. However, for copula parameters, the MPL is preferred and the corresponding AIC becomes more precise than the one based on ML (similarly for BIC). MPL formulation is employed in several studies (see Joe, 2014, and references therein). In addition to AIC and BIC, one can use the cross-validation copula information criterion. However, based on comparison in a bivariate simulation study, AIC and cross-validation are found to be overall almost similar. For theoretical developments related to model selection for copulas, the interested reader is referred to Grønneberg and Hjort (2014).
- *Uncertainty assessment.* While uncertainty assessment is routinely implemented in univariate analysis, it is seldom addressed in the multivariate context. Uncertainty may affect copula parameter estimation, copula selection, and return period estimation. The relevance of dealing with uncertainty for reliable multivariate quantile estimation is analyzed in several studies (e.g., Serinaldi, 2013; Dung et al., 2015), where the usual lack of long data records for multivariate analysis is underlined. Lately, Bayesian approaches have been proposed to account for uncertainty in model parameters and return period estimations in the multivariate framework (e.g., Kwon and Lall, 2016; Sadegh et al., 2018; Liu et al., 2020).

Several packages are available under the free software R (R Core Team 2020) for addressing copula-based frequency analysis; some of the most relevant ones are listed in Table 2.

3.4. Challenges and open problems

As described above, a significant contribution to multivariate hydrological frequency analysis using copulas has been produced in the last two decades. In this Section, we highlight some additional aspects of multivariate analysis that are emerging or still require efforts from researchers.

A warning emerging from the literature is that the analysts too often limit their attention to a few copula functions, typically Archimedean, while, as shown here, the possible options are diverse, offering the opportunity to reach a better modeling outcome of the data sample. Furthermore, apart from the copula families mentioned above, it is important to mention multi-parameter copulas. Although multi-parameter copulas have not been fully explored, they are attracting more attention in recent years (e.g., Salvadori and De Michele, 2010; Requena et al., 2016; Ben Nasr and Chebana, 2019; Sadegh et al., 2017; Joe, 2014). In principle,

most estimation methods are valid for multi-parameter copulas, but most applications in hydrology literature are limited to one-parameter copulas. Brahimi and Necir (2012) extended the MM-based method to multi-parameter copulas whereas Brahimi et al. (2015) proposed a multivariate L-moment method. The latter has some interesting features for the case of short sample sizes such as in frequency analysis. Note, however, that using multi-parameter copulas when one-parameter copulas would suffice generally implies an increased estimation uncertainty. Bayesian approaches are also used to estimate the parameters of multi-parameter copulas and their underlying uncertainty.

By analogy with the univariate setting, the stationarity assumption could fail in the multivariate framework due to changes in urbanization, land use/cover or climate. Hence, to be more realistic and for an accurate risk estimation, the multivariate non-stationarity modeling should be considered. This is a recent and emerging topic in statistical hydrology with a growing number of studies, including Chebana and Ouarda (2021) for floods, Jiang et al. (2015) for low-flow series, Kwon and Lall (2016) for droughts, and Feng et al. (2020) for flood coincidence risk. Conversely, the relaxation of the independence hypothesis that allows to incorporate additional data for inference in the univariate setting, still requires additional theoretical developments in the multivariate one. Indeed, as mentioned at the beginning of Section 3 (testing assumptions), the serial independence condition is a requirement for multivariate analysis.

Table 2 – Packages for multivariate, copula-based frequency analysis and modeling.

Name	Brief description	Repo.	Link	Authors
copula	Multivariate Dependence with Copulas	CRAN	https://CRAN.R-project.org/package=copula	Kojadinovic and Yan, 2010; Hofert and Maechler, 2011; Hofert et al., 2020
VineCopula	Statistical Inference of Vine Copulas	CRAN	https://CRAN.R-project.org/package=VineCopula	Nagler et al., 2019
MvCAT	Multivariate Copula Analysis Toolbox	UCL.edu	https://amir.eng.uci.edu/MvCAT.php	Sadegh et al., 2017
MhAST	Multi-hazard Scenario Analysis Toolbox	UCL.edu	https://amir.eng.uci.edu/MhAST.php	Sadegh et al., 2018; Moftakhari et al., 2019
MSDI	Multivariate Standardized Drought Index (MSDI)	CRAN	https://search.r-project.org/CRAN/refmans/drought/html/MSDI.html	Hao and AghaKouchak, 2013
corTESTsrd	Significance Testing of Rank Cross-Correlations under SRD	CRAN	https://CRAN.R-project.org/package=corTE	David Lun, Svenja Fischer, Alberto Viglione

			STsrd	
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4. Time series analysis and simulation

The rationale of time series modeling and simulation in hydrology is to resemble and reproduce the characteristics of a variable of interest for simulation and forecasting applications. This is typically performed by describing the historical evolution of the variable in time. Thus, records can be usefully extended by using synthetic data generated by stochastic models, which is known as Synthetic Hydrology (Benson and Matalas, 1967; Matalas, 1967). Artificial data sets with adequate length are created from the characteristics of existing observations (which are insufficiently long for a reliable design or assessment of water systems), potentially providing a huge number of random sequences with the observed statistical characteristics; the readers are referred to Table 3 for a list of R packages (R Core Team, 2020) available for hydrological simulation. The stationarity hypothesis is the major assumption, which presumes a future with a non-dynamic behavior in terms of statistical moments and correlation of the past.

Time series modeling of hydrological variables has a history of about a century and continues to evolve into intense research. Markov chains were proposed at the beginning of the 20th century for streamflow simulation; then, with the introduction of the autoregressive (AR) models by Thomas and Fiering (1962) and Yevjevich in 1963, the formal development of stochastic modeling has started. Early literature reviews on these early studies clarify the historical development of time series modeling in hydrological studies; the readers are referred to Lawrance and Kottegoda (1977), Rodriguez-Iturbe et al. (1972), Mejia et al. (1972), and references therein.

The historical focus on stochastic streamflow models (i.e. Thomas and Fiering 1962; and Matalas 1967) was to enable hydrologists to evaluate the reliability, vulnerability and resilience of future water resource systems. Such computational tools and principles also enabled a more complete integration of uncertainty into water management decision making and have been in common use by several agencies worldwide for over 50 years (see Vogel, 2017, for a brief review). Although the variable of interest is the discharge in a river cross-section, the continuous synthetic simulation methodology based on a stochastic model of precipitation and other meteorological variables, called weather generators, is increasingly used. Many studies can be found in the literature that follow this approach with different nuances. Among the more modern approaches, it is relevant to mention the stochastic weather generators by Steinschneider et al. (2019) for multivariate/multisite weather variables (i.e. rainfall and temperature) which can capture low-frequency climatic variability for use in water resource vulnerability assessments.

In a pioneering work, Cameron et al. (1999) combined a modification of the also pioneering weather generator developed by Eagleson (1977) with a semi-distributed hydrologic model. This formed the basis for the development of Stochastic Watershed Modeling (SWM). SWMs are deterministic watershed models implemented using stochastic meteorological series, model parameters and model errors, to generate ensembles of streamflow traces that represent the variability in possible future streamflow. By combining deterministic watershed models, which

are ideally suited to account for anthropogenic influences, with recent developments in uncertainty analysis and principles of stochastic simulation, SWMs are promising tools to accommodate climate, land use or other forms of change (see Vogel (2017) for a comprehensive discussion), and will be certainly the focus of future works. Conversely, the remainder of this Section is dedicated to purely stochastic modeling approaches, that were of main interest of the STAHY community in the past years.

Through this journey, there are several divisions in time series modeling. The basic classification is deterministic (like trends or jumps, periodicity, and seasonality) and stochastic (based on stationarity and ergodicity) components. Further, the modeling is extended to a single site and variable (univariate) or multiple sites and variables (multivariate and multi-site). In addition, depending on the state of the variable, the modeling is divided into discrete, continuous and mixed types. Finally, the most basic classification in terms of stochastic modeling is parametric and non-parametric approaches. The parametric approaches consist of models such as autoregressive to models based on machine learning algorithms. The nonparametric methods typically consist of kernel density and bootstrap techniques. Subsequent sections provide details only about the statistical parametric models being aware of the recent impressive development and of the potentiality of machine learning and data science tools, which may be the subject of ongoing work in the ICSH Commission.

The introduction of the Hurst phenomenon further advanced stochastic modeling (Hurst, 1951), yet it was (and probably still is) controversial during the early stages (Klemeš, 1974) among hydrologists. Though Hurst introduced these phenomena in the early 50's, Kolmogorov introduced the same concept mathematically in the early 40's. Long-term persistence and fractional Gaussian noise models were mainly popularized by Mandelbrot and Wallis (1968) and, later, by Beran (2017) in hydrology. In view of extensive arguments related to the interpretation of Hurst phenomena and uncertainties in the estimates of the Hurst exponent, simple models such as AutoRegressive Moving Average (ARMA) models capable of reproducing simple statistics are used by early hydrologists (Salas, 1980). Subsequently, several models have been proposed, such as the fractional Gaussian noise models, mixture models such as ARMA-Markov models, Fractionally AutoRegressive Moving Average (FARMA) or Autoregressive Fractionally Integrated Moving Average (ARFIMA) models, disaggregation models, models for intermittency, and general mixture models (Montanari et al., 1997).

Table 3 – Packages for time-series analysis and modeling.

Name	Brief description	Repo.	Link	Authors
LPM	Linear Parametric Models Applied to Hydrological Series	CRAN	CRAN - Package LPM (r-project.org)	Corrado Tallerini, Salvatore Grimaldi
CoSMoS	Complete Stochastic Modelling Solution	CRAN	CoSMoS R Complete Stochastic Modelling Solution (r-project.org)	Simon Michael Papalexiou, Francesco Serinaldi, Filip Strnad, Yannis Markonis, Kevin

				Shook
MMM and MRD	Multisite Markov Model (MMM) for rainfall generation, and its extension using exogenous predictor variables for downscaling (MRD)	UNSW	Multisite Markov Model (MMM) Multisite Rainfall Downscaling (MRD)	Raj Mehrotra, Ashish Sharma
SAMS2007	SAMS Stochastic Analysis, Modeling and Simulation	USBR	http://www.sams.colostate.edu/	Sveinsson et al. (2007)

4.1. Single-site modeling

In the following we provide a state-of-the-art review on parametric approaches, focusing on discharge and rainfall simulation.

4.1.1. Streamflow simulations

The first approach for modeling hourly and daily streamflow time series was the AutoRegressive models (AR). Thomas and Fiering (1962) introduced a streamflow generation model which is an AR model for generating monthly streamflow of the Clearwater River (USA). After that, several models have been developed for hydrologic time series modeling. These models consider that a variable value at a specific time instant is related to the corresponding value at the previous instance(s). Streamflow of larger scales (week, month, season) can be described by stationary stochastic models after being seasonally standardized. The low-order AR and ARMA have been the most popular models for annual streamflow simulation (Box and Jenkins, 1976). Hirsch (1979) made a comparison of six different single-site data generation mechanisms concluding that the autoregressive moving average model was superior to the autoregressive model. Box and Jenkins (1976) proposed the multiplicative models, in which the trend and seasonal components are multiplied and then added to the error component, to capture seasonal and annual statistics. However, these did not include parameters for the periodicity. When a periodic structure is present, the Periodic AutoRegressive (PAR) or the Periodic AutoRegressive Moving Average (PARMA) models (Salas and Obeysekara, 1992) are more suitable. The latter has a more flexible correlation structure and preserves seasonal and annual statistics, at the expense of the number of parameters. The need to transform the time series into Normal is a restraint of the PARMA and its multiplicative version. To overcome this limitation, a model with periodic correlation structure and periodic gamma marginal distribution, i.e., the PGAR(1) model, has been proposed (Fernandez and Salas, 1986). Other versions, modifications, and developments of these models are the autoregressive integrated moving average (ARIMA) and the autoregressive fractionally integrated moving average (ARFIMA or FARMA) models (Oliveira and Maia, 2018).

Other approaches were developed to account for short-term physical characteristics of flow (ascension and recession curve) together with the long-term statistical characteristics (mean, variance, lag-one, and higher lag correlation coefficients); see Claps et al. (2005). Among them, the shot noise models are based

on overlapping pulses which represent the autocorrelation structure and are mostly used for variables with a strong and repetitive autocorrelation; the shot noise model has been used because of its ability to reproduce the physical behavior and hydrological aspect of the streamflow process.

Streamflow processes depict an intermittent behavior (similar to rainfall records) when the contribution of the hydrological basin to the river is significantly reduced due to lowered groundwater levels and no substantial snowmelt during the rainless season. Intermittency is effectively felt in arid and semi-arid regions (Salas and Fernandez, 1993). Yevjevich (1984) summarizes the approaches used for modeling intermittent time series as (i) spell process, (ii) truncated process, and (iii) 1-0 approach. Another kind of model used for the daily streamflow is based on transition probabilities to understand the state of the stream (whether it has flow or not in a particular day; and whether it increases or decreases); a transfer function model using a wet/dry Markov chain was proposed by Treiber and Plate (1977) where a pulse is assigned in a wet day by using a modification of the exponential distribution.

Annual, monthly, and daily multisite streamflow simulation is also achieved by parametric disaggregation models (Kumar et al., 2000) and nonparametric disaggregation models (Lee et al., 2010; Nowak et al., 2010). Other examples include a semiparametric model for daily streamflow by Srinivas and Srinivasan, (2005), a parametric multisite stochastic simulation framework for the generation of seasonal timeseries reproducing sub-annual statistics, short-term memory and long-term persistence (i.e. over year scaling of annual averages) by Langousis and Koutsoyiannis (2006), wavelet methods (Keylock, 2012), entropy methods (Srivastav and Simonovic, 2014), empirical decomposition methods (Lee and Ouarda, 2012), copula methods (Chen et al., 2019), the moving block bootstrap (Srinivas and Srinivasan, 2005) and k-nearest neighbor bootstrap (Lall and Sharma, 1996).

Simulation models grow in complexity as temporal resolution increases; i.e., a daily streamflow simulation model is expected to be more demanding than an annual model. This is not only because of the increasing amount of data involved when temporal resolution increases, but also because of the emergence of finer detail upon closer examination of the physical process. By delving into the time interval, a critical understanding of the temporal asymmetry (or time irreversibility; see Carsteanu and Langousis, 2020; Koutsoyiannis, 2021) in the rising and falling limbs of the daily streamflow hydrograph emerges. This is due to the physics behind the streamflow process which has different physical drivers for the ascension and recession curves of the hydrograph at a daily time step. It is, therefore needed to conserve the temporal asymmetry in the streamflow generation models (Serinaldi and Kilsby, 2016). This is particularly important as a simulation does not only replicate the statistical measures but it also regenerates the physical structure of the daily streamflow process.

4.1.2. Rainfall simulation

Rainfall can be modeled either by considering the process as continuous (point process and cluster models), by using approaches of cumulative precipitation over non-overlapping time intervals aggregating rainfall at the desired time scale (i.e.

hourly, daily, monthly), or by using mixed-type distributions to transform Gaussian time series to preserve marginal and correlations. Typical examples are the Markov chain and the alternating renewal models. Multifractal simulation techniques are also a popular tool for temporal rainfall disaggregation of rainfall data (see e.g. Veneziano and Langousis, 2010 for a review).

One of the first theories in modeling precipitation as a continuous process is the point process theory (e.g., Cox and Isham, 1980). Based on this, the number of storms, the arrival rate and the rainfall amount for each storm are considered and simulated as independent random variables. This Poisson approach was modified to consider rainfall to have a random duration and intensity, independent from one another and usually exponentially distributed (Poisson rectangular pulse models); the storms may overlap so that the cumulative process is autocorrelated. The Poisson-based model, although flexible for a particular level of aggregation, presents limitations when studying a range of time scales (Rodriguez-Iturbe et al., 1987). The clustered point process-based models, where a cluster of activities starts at every point of a point process, offer more realistic representations of rainfall and can represent multiple timescales at once. Two such models are the Neyman-Scott and Bartlett-Lewis; the Poisson cluster process-based models are common structures for the generation of sub-daily rainfall time series, as rectangular profiles are flexible in approximating discrete rainfall which is aggregated over time intervals of 1 hour or more (see, e.g., Cowpertwait et al., 2007). Subsequently, several studies (e.g., Velghe et al., 1994; Kilsby et al., 2007; Kim and Onof, 2020) investigated the performance of both the models and provided modified versions able to better catch, e.g. the autocorrelation, skewness, extreme values, etc., at different time scales. Among the available models, we recall the RainSim rainfall simulator based on the Generalized Neyman-Scott Rectangular Pulses developed by Cowpertwait in 1995, that was used for single-and multi-site applications, and later improved by Burton et al. (2008). Both rectangular pulse models, either in their original form or with modifications, were found to satisfactorily represent rainfall processes for a range of time scales for the UK, Scotland, Belgium, Switzerland, Spain, Australia, New Zealand, Ireland, South Africa, Greece, Italy, and the USA (Kossieris et al., 2018).

The Markov Chain (MC) model (or Markov process) describes a sequence of events whereby the present condition depends only on the antecedent state. The MC model is characterized by the transitions, which are the changes of state, and the transition probabilities. In the first-order MC, the probability of daily rainfall is conditioned on the status (wet or dry) of the previous day. The most substantial advantage of the model is the fact that it identifies the seasonality in daily rainfall occurrence which can be described adequately by the process (Stern and Coe, 1984), although the model has failed to fit the observed data in some cases. Some studies have noted that the method underestimates the dry spells (Sharma and Mehrotra, 2010; Wilks and Wilby, 1999). Usually, Markov chain models of higher orders can overcome these issues (Hayhoe, 2000; Wilks, 1999). Higher-order MC models are based on wet day probabilities of a few consecutive days, thus improving the model's "memory". The number of transition probabilities/parameters required increases exponentially as the order increases. Although these models improve the representation of interannual variance they still do not always manage to represent climatic variability (Sharma and Mehrotra,

2010). To improve the simulation of dry spells, the use of ‘hybrid-order’ Markov models is proposed, where the “memory” extends further back in time but only for the dry spells (Wilks and Wilby, 1999); to better represent rainfall clustering in time, the multi-state Markov chain model is used to simulate both rainfall occurrence and the number of different precipitation bands (Haan et al., 1976). These models require a large number of parameters and long data records. Finally, non-stationary Markovian dependence is provided by the modified Markov model, which allows for the preservation of rainfall statistics up to the decennial scale, by conditioning the Markov chain parameters on the number of past wet days (see, e.g., Oriani et al., 2018 and references therein). Over the past few decades, several stochastic rainfall generators have been proposed based on MC models for the rainfall occurrence combined with a parametric probability distribution for the rainfall amount on a wet day; see, among others, Weather GENERator (WGEN) by Richardson (1981), and versatile stochastic daily weather generator (WeaGETS) by Chen et al., (2012).

Another category of rainfall time-series simulation models uses a simple renewal process to describe the alternation of wet and dry conditions. The term renewal implies independence between wet and dry period lengths. For the representation of wet and dry spells, logarithmic series, the truncated negative binomial distribution, the truncated geometric distribution, and other semi-empirical distributions have been proposed (Wilks and Wilby, 1999). Another probability distribution describes the rainfall amount. The approach allows for the direct estimation of composite precipitation events but cannot depict the seasonality of the rainfall occurrence (Srikanthan and McMahon, 2001).

As early as in the mid-60s, researchers identified the fractal behavior of time series, according to which an object can be subdivided into reduced-size copies of the whole (Mandelbrot, 1982). Based on the multifractal theory, fluctuations at a given scale can provide information on those at other scales via scale invariance. Statistical moments are associated with a scale parameter through a log-log linear relationship; thus, multifractal models are preferred for their ability to correctly reproduce the strongest events. The underlying idea of this framework is that these fields are the result of an underlying random multiplicative cascade process (Schertzer and Lovejoy, 1987). Multiplicative cascade models can be used for temporal rainfall disaggregation of daily data to generate rainfall time series of high temporal resolution. First introduced by Yaglom (1966), they have appeared to be promising and therefore have received significant attention ever since (e.g., Menabde et al., 1997; Deidda, 2000; Veneziano and Langousis, 2005b, 2010; Langousis and Veneziano, 2007; Gaume et al., 2007). Multifractal approaches can be pulse-based, non-pulse-based using wavelet decompositions, and non-pulse-based using discrete or continuous multiplicative cascades (Flores, 2004). Other works related to time series fractality in hydrology (Adarsh et al., 2020) include double trace moments (Tessier et al., 1996), wavelet transform modulus maxima (WTMM) (Kantelhardt et al., 2003), extended self-similarity (ESS) (Dahlstedt and Jensen, 2005), arbitrary order Hilbert spectral analysis (AOHSA) (Huang et al., 2009) to mention a few.

Recent approaches in univariate, multivariate, random field simulations of rainfall focused on generating time series or random fields that explicitly preserve any desired marginal distribution at different locations and seasons, as well as any desired correlation structure (Papalexiou, 2018; Papalexiou et al., 2021; Papalexiou

and Serinaldi, 2020). The scheme comprises five steps, as graphically demonstrated in Figure 2; it is clearly generic and allows simulation of time series having any marginal distribution and autocorrelation and can be used for many different hydroclimatic processes such as relative humidity, wind speed, river streamflow, or any process having discrete and binary marginal such as the number of extremes per year or wet-dry sequences (for more details see Papalexiou, 2018).

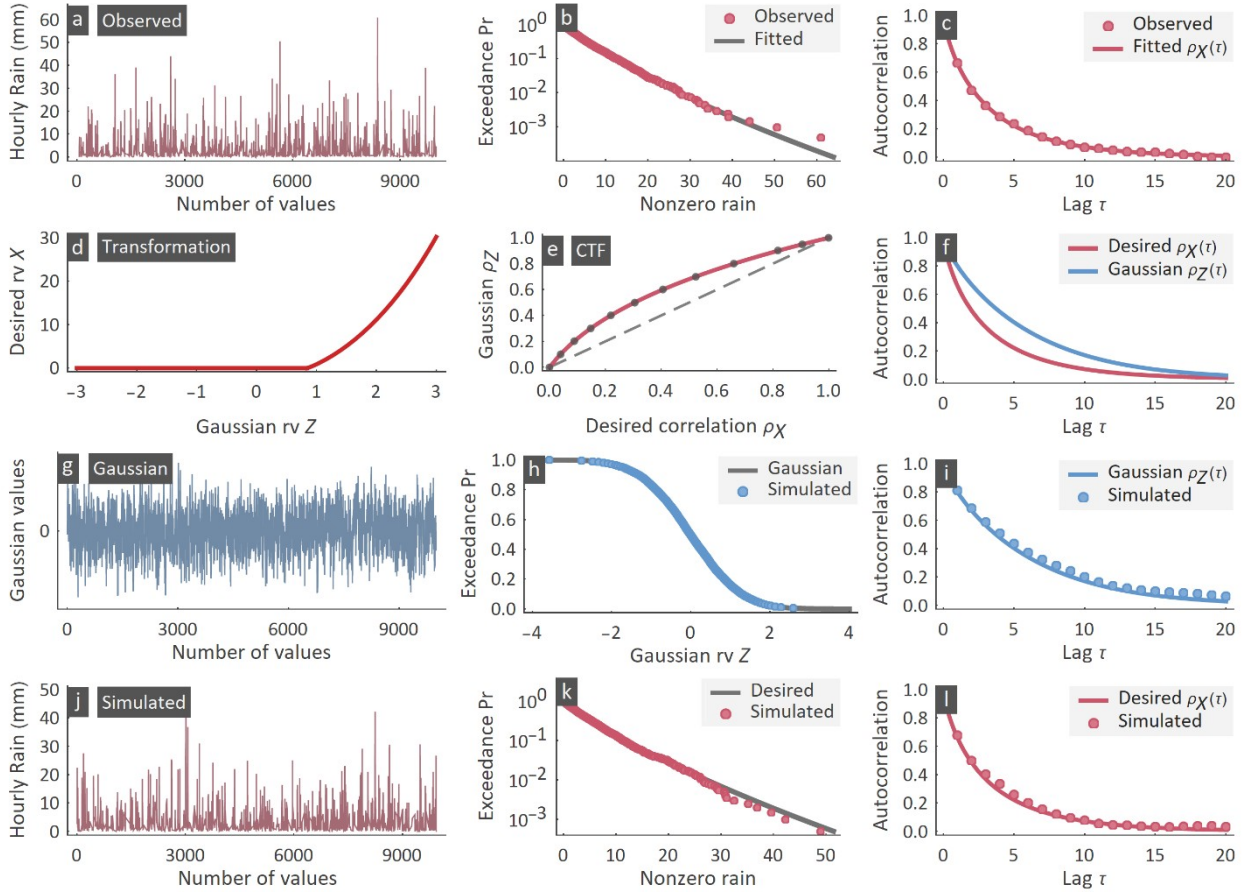


Figure 2 – Step-by-step graphical demonstration of stochastic simulation that preserves explicitly a desired marginal distribution and correlation structure. (a, b, c) Observed precipitation time series and the fitted parametric distribution and autocorrelation structure; (d) transformation of Gaussian values to the desired mixed-type fitted distribution and (e, f) the corresponding correlation transformation function (CTF) and estimated autocorrelation structure of the Gaussian process; (g, h, i) generated Gaussian time series, its marginal and correlation structure; (j) final simulated time series that indeed have (k, l) the desired marginal distribution and autocorrelation structure.

Recently, the development of continuous hydrological modeling has made rainfall simulation models more important, as they constitute the input in this promising approach (Grimaldi et al. 2022). However, it is still not available to the community a unique approach easy to apply. A challenge for the near future is to identify the best rainfall simulation approaches for specific hydrological applications providing user-friendly tools applicable without a restricting statistical background. This is a subject of current interest of the ICSH commission that will be addressed in future publications.

In addition to the parametric approach, it is worth mentioning that the nonparametric methods offer attractive alternatives since they can capture nonlinear and non-Normal data characteristics. Nonparametric regression refers to

a group of approaches that are used to fit a curve when little a priori knowledge exists about its shape (Altman, 1992). Running averages have been used since the late 19th century for determining time series trends by De Forest, as mentioned in the work of Wolfenden of 1925. Later, local location estimators like the kernel (e.g., Parzen, 1962) and the nearest-neighbor regression estimators (e.g., Cover and Hart, 1967) were introduced. The conditional kernel density estimation derives a probability density function from histogram data. The technique allows the creation of a smooth curve (empirical probability density estimate) given a set of data. In the kernel density estimation for discrete random variables such as rainfall (Lall, 1995), wet and dry spell lengths are considered as an integer number of days and the sample relative frequencies are estimated. These relative frequencies are then smoothed with a kernel estimator. The kernel method is superior to the maximum likelihood estimator which yields the relative frequency directly, as it allows extrapolation of probabilities to spell lengths, and has higher MSE efficiency (Rajagopalan and Lall, 1995). Some kernel estimators are the geometric, the Maximum Penalized Likelihood Estimator, the estimator by Hall and Titterington, and the Discrete Kernel estimator (see Rajagopalan et al., 1997 and references therein).

When a model is applied at a time interval shorter than a year or month; e.g., week or day, parameterization becomes computationally costly, because the seasonality comes front more effectively. This brings the problem that one single value of a parameter cannot be applicable over the year; i.e., monthly, weekly, or even daily parameterization is needed. This is a big burden over the modeling approach that can be overcome by fitting a seasonal function to the parameters such as the Fourier series (Aksoy and Bayazit, 2000).

4.2. Multisite modeling

4.2.1. Multisite streamflow generation

It is quite common for river flows in the same or close basins to exhibit significant cross-correlations among their tributaries since they receive runoff from the same parent rainfall. Therefore, multi-site models which preserve cross-correlation between sites are logical (Matalas, 1967). Some of the models mentioned above can be extended to multiple sites, i.e., the multivariate AR(1) and ARMA(1,1) are usually adequate for the annual time scale. Multivariate ARMA models often result in complex parameter estimation and model simplifications have been suggested such as the contemporaneous ARMA (CARMA) (Salas, 1980). ARIMA models have also been applied for the multisite case. The Markov cross-correlation pulse model has been used to extend single site streamflow generation to multiple sites, preserving high daily cross-correlations (Xu et al., 2003). A hybrid seasonal Markov chain model was also used at multiple sites by Szilagyi et al. (2006). The model used shot noise models in a Markov chain-based framework, along with a conceptual model for flow recession, managing to generate long time series of daily flow which preserve long-term statistics. Medda and Bahr (2019) provide a list of models used for the multisite case, such as the hybrid stochastic model of Srinivas and Srinivasan (2005) with a parsimonious periodic parametric model and moving

block bootstrap for resampling of the residuals, and the models found in Wang and Ding (2007), Hao and Singh (2013), and Srivastav and Simonovic (2014).

4.2.2. Multisite rainfall generation

Numerous studies have dealt with the spatial dependence of precipitation in space-time stochastic models under parametric (Papalexiou and Serinaldi, 2020; Papalexiou et al., 2023), semiparametric, and non-parametric frameworks (Sharma and Mehrotra, 2010). Multisite rainfall generation models can be broadly categorized into conditional models (hidden Markov models), extensions of Markov-chain models, and random cascade models (Srikanthan and McMahon, 2001).

In the hidden Markov models, the multisite rainfall is simulated conditional on the weather states and/or atmospheric circulation patterns so that the effects of large-scale atmospheric circulation are incorporated into local weather (Hughes and Guttorp, 1994; Zucchini and Guttorp, 1991). In the hidden Markov model of Zucchini and Guttorp (1991) the climate process follows a Markov chain. Other versions of the model are the ones of Bárdossy and Plate (1992), Wilson et al. (1992), and Charles et al. (1999). Wilks (1998) extended the first-order Markov chain with the two states and a mixed Exponential distribution for the simultaneous generation of rainfall at multiple locations by having individual models fitted to each site and using spatially correlated random numbers to introduce spatial dependence. Jothityangkoon et al. (2000) introduced a space-time model with a temporal first-order, four-state Markov chain and a spatial model based on a non-homogeneous random cascade process, for the generation of daily rainfall. The model manages to reflect the spatial patterns of the long-term mean of all time-scales, the spatial distribution of the wet fraction, the statistical characteristics of storm arrivals and interarrival times, as well as the exceedance probabilities of rainfall but underestimated the mean number of wet days and the mean wet spell lengths during winter months. To avoid the use of discrete weather states in continuous rainfall generation, Langousis and Kaleris (2014) and Langousis et al. (2016b) proposed and applied a scheme for stochastic simulation of daily rainfall conditional on upper-air predictor variables. While the scheme didn't involve any type of seasonal modeling, it was found to accurately reproduce several rainfall statistics at seasonal and annual time scales (wet day fractions, the alternation of wet and dry intervals, the distributions of dry and wet spell lengths, the distribution of rainfall intensities in wet days, short-range dependencies, the distribution of yearly rainfall maxima, among other), as well as the dependence of rainfall statics on the observation scale.

Other approaches used for multisite rainfall generation include the Generalized Linear Models (GLM) (Chandler and Wheeler, 2002), the reshuffling approach-based models (Clark et al., 2004), models that preserve exactly the marginal distributions and correlations (Papalexiou, 2018; Papalexiou and Serinaldi, 2020), and nonparametric models like the k-nearest neighbor approach (Buishand and Brandsma, 2001), and semi-parametric models that parameterize the rainfall occurrence generation process while using nonparametric methods to characterize rainfall amounts (Mehrotra and Sharma, 2007). Fu et al. (2018) provide a comparison between four multisite weather generators: (1) the Generalized Linear Model for daily Climate time series, based on generalized GLMs, (2) the Stochastic

Climate Library which uses a first-order two-state Markov chain, (3) the Multi-site precipitation generator, based on the approach of Wilks (1998), and (4) the Multi-site Auto-regressive Weather GENERator based on the theory of vector auto-regressive models. They note that all models reproduce the daily, monthly, and annual rainfall, extremes, and dry/wet spell lengths reasonably but also simulate a large range of variability.

4.3. Change detection in hydrological time-series

As premised in Section 2.3 stationarity may be questionable, at least for some hydrological time series (Milly et al., 2008, 2015). However, non-stationarity is hard to detect and often false assumptions on the underlying process can lead to falsely rejected hypotheses for non-stationarity tests (see, e.g., Lins and Cohn, 2011 and Serinaldi and Kilsby, 2015). In the following we review some recent techniques for non-stationary analysis and simulation, emphasizing explicitly the high uncertainty when dealing with non-stationarity in short time series.

For change analysis, the detection of irregularities, jumps, changes, and trends is of the highest importance. For many stochastic models, non-stationarity - when detected - has to be removed before application, while recently developed stochastic models are able to include it in the model structure; either way, it is essential to know the time of occurrence of non-stationarities. To reliably differentiate non-stationarities from simple random effects in time series, statistical tests are applied that do or do not reject the hypothesis of stationarity (the null hypothesis) according to a given significance level, typically taken to be 5%. This corresponds to Type I error, which is the probability of detecting a change when it does not exist (societal over-preparedness). Type II error, related to statistical power, is the probability of missing the change when it exists; even though it informs us about the probability of under-preparedness, which is a fundamental issue for society, it is rarely considered in the analysis (Vogel et al., 2013). See also Prosdociimi et al. (2014) for a discussion on the importance of correctly specifying the null and alternative hypothesis in non-stationarity testing and how this relates to statistical power.

Common tests can be categorized according to some of their properties such as whether they are parametric or non-parametric (i.e. if an assumption on the data distribution is made), and how conservative, powerful, efficient, or robust they are. The dependence structure for which the test was constructed must also be differentiated. Most tests can be applied for the case of independent and identical distributed data (i.i.d.). However, if short- or long-range dependence occurs, the limit distributions and the test statistics have to be extended (see, e.g., Serinaldi et al., 2018). Classical examples of Short-Range Dependent (SRD) processes are mixing processes or Markov-processes. Long-Range Dependence (LRD) is much harder to detect with respect to the short-range case, especially when the sample analyzed spans over a short observation period, as it is often the case for hydro-meteorological records. However, many studies argue that flood and precipitation processes are characterized by long-range dependence in terms of long-term cyclic behavior (Szolgayova et al., 2014; Koutsoyiannis, 2021) yet other studies in long streamflow records do not verify the existence of long-range dependence (Markonis et al., 2018), see also the discussion in the introduction of Section 4.

Non-stationarities in time series are basically differentiated into two categories: change-points and trends. The first category, change-points, applies to the case where an abrupt change in the distribution of the random variables occurs at one point in time. The second category, trends, applies to continuous and monotone changes in the distribution. An in-depth introduction to the statistical methods for the detection of non-stationarity can be found in Helsel and Hirsch (1992).

Many distribution properties can change abruptly at any given point in time, e.g., due to the impact of some exogenous factors or a change in the measuring of the process: change point tests aim to detect these possible changes. Time points where changes take place are called *change points*; the interval included between two change points is a *segment*, and the procedure by which the segments of a time series are determined is called *segmentation*. Segmentation of a time series simply means dividing a given number of observations into subseries with statistical characteristics that are similar within each subseries and different between subseries (Salas et al., 1980; Helsel and Hirsch, 1992). This is also called jump analysis and can be considered a change point detection problem for which statistical tests and Bayesian procedures are available (Pettitt, 1979; Alexandersson, 1986; Seidou et al., 2007). Many segmentation methods and a very extensive bibliography are presented in Basseville and Nikiforov (1993); additionally, recent segmentation procedures are available in the literature (Hubert, 2000; Kehagias, 2004; Kehagias et al., 2006; Gedikli et al., 2010). The simplest case is the segmentation with regression-by-constant in which it is aimed to determine the change points or boundaries where the average of the current segment is statistically different than the average of the next segment as well as that of the previous one. This shift or jump may either be positive or negative. Not only segmentation with regression-by-constant but also segmentation with regression-by-lines or higher-order polynomials can be used (Kehagias et al., 2006).

Common change-point tests focus on changes in mean, variance, and correlation. Corresponding change-points can be identified at the time when the test statistic reaches its maximum. Change-points in the mean refer to abrupt changes in the mean value of the underlying distribution. The simplest test statistic is based on the CUMulative SUMs (CUSUM) of the series values before and after the change point. CUSUM tests for a change in mean exist for i.i.d., SRD, and LRD time series. Many CUSUM tests are non-parametric and efficient, but not robust. To overcome this problem, the robust Wilcoxon (Mann-Whitney) test was developed. Again, statistical theory for this test exists for i.i.d., SRD and LRD time series (see Dehling et al., 2013, and the references therein). Another robust test for a change in the mean is the Pettitt (1979) test, usually applied for i.i.d. data. Changes in variance are less often investigated in hydrology. Common tests are the parametric CUSUM test (Inclan and Tiao, 1994) which can be applied to i.i.d., short- and long-range dependent (SRD and LRD) data and the robust, non-parametric test based on Gini's mean difference which can be applied to i.i.d. and SRD data (Gerstenberger et al., 2020). To test for a change in the correlation structure, tests based on correlation coefficients like Spearman's Rho or the Pearson coefficient are applied. These tests exist for independent and weakly dependent time series (Wied and Galeano, 2013; Dehling et al., 2017). Note that detecting a change in e.g. the mean does not imply that it is the only statistic that changes over time; as pointed out in Section 2.3, a

thorough preliminary analysis is necessary to understand which structure is most appropriate to model change.

In contrast to change-points, trends assume a monotonic, continuous change in the central tendency (often taken to be mean) of the time series. The most common trend tests are the Mann-Kendall test and the Cox-Stuart test: both these tests are non-parametric and therefore can be applied to data series without assuming that they follow specific distributions. The Mann-Kendall test can be applied to independent data as well as weakly dependent data (Cabilio et al., 2013) or the special case of seasonally impacted data (Zhang et al., 2016). Notice that the Mann-Kendall test corresponds to computing the Kendall correlation coefficient for the record under study and the time index. The Cox-Stuart test (e.g., Rutkowska, 2013) typically requires longer observation records than the Mann-Kendall test and has less power. Moreover, the presence of autocorrelation limits the application of this test. Pre-whitening often reduces the power of trend tests or falsely raises their Type I error rates (Bayazit and Önöz, 2007; Wang et al., 2015). Either ignoring the effect of autocorrelation or dealing with it without choosing adequate methods will result in inaccurate detection results. A robust trend detection strategy should involve the investigation of the autocorrelation structure of the data and the selection of the corresponding method that keeps a balance between maintaining a low Type I error and a relatively strong power of trend detection (e.g., O'Brien et al., 2020). Trend tests can be informative on whether a change in the mean of the time series has occurred, but cannot quantify the actual change. They are therefore often coupled with the Theil-Sen slope which provides a robust estimate to quantify the change which occurred over time in the mean of the time series (e.g., Yilmaz and Tosunoglu, 2019). Notice that a change in the mean can have an impact on the results of a trend test and vice versa.

At large scales, the detected trends identified at several sites could be statistically non-significant at a regional scale, where several distinct issues can be investigated. The most thoroughly studied is field significance: when a test is repeated with a given significance level on several locations, the aim is to determine the minimum number of locally significant trends to conclude, with a regional significance level, that the changes are not all due to chance. The second aspect involves the consistency of changes detected within a given region. Exploiting the concept of regionalization may be a step forward, as presented in Section 5. Furthermore, the spatial correlation between time series should be considered. See for example Renard et al. (2008) or Yue et al. (2003) for approaches to trend testing in a large region.

In addition, identifying the cause or physical underpinning of detected trends is often the main objective. There is a wide range of methods for the detection and attribution of changes designed for individual and compound hazards (Chiang et al., 2021; Easterling et al., 2016; Slater et al., 2021b; Chiang et al., 2022). The partial Mann-Kendall test (PMK), for instance, can be used to test if a detected trend in a hydrological time series is significant after removing its correlation with a covariate variable (Libiseller and Grimvall, 2002).

If a distribution can be assumed for the data, it is possible to construct change point and trend tests within a parametric framework. If, for example, one wishes to test whether an abrupt change occurs in a given year in the location parameter it is

possible to compare the goodness of fit of two models: one in which the location parameter is assumed to be constant and another in which the location takes to different values before and after a specified change-year. The comparison might use the goodness of fit criteria such as AIC or be based on a likelihood ratio test between the two nested models (Kundzewicz and Robson, 2004). Katz et al. (2002) offer an introduction to this type of parametric models with applications for hydrological extremes. Similar approaches can be employed to construct trend tests and investigate whether changes can be detected in one or, as expected, more parameters of the parametric models, for example, scale and location. Parametric approaches can also be further extended to allow for not only linear or monotonic changes in the parameters. For example, Villarini et al. (2009) and Slater et al. (2021a) applied the Generalized Additive Models for Location Scale and Shape (GAMLSS) to investigate possible changes in extremes. See also Debele et al. (2017) for a discussion on the usability of GAMLSS in the analysis of hydrological extremes.

Detection of changes in hydrology is a difficult task. The often skewed or zero-inflated data with unknown dependence structure and distribution require a detailed a priori analysis (Kundzewicz and Robson, 2004) and cross-correlation has to be considered if spatial data sets are evaluated (Douglas et al., 2000). The test statistics with correct assumptions on dependence and distribution of the data have to be selected from a pool of available tests. When detecting a change-point, it is necessary to determine its origin. Without attribution, i.e. the clarification of the deterministic causes, a change-point detection is of small value for hydrological purposes. Moreover, evidence supports the significance of the findings. For example, changes in mean in discharge data can be related to anthropogenic impacts like the building of dams (Seibert and McDonnell, 2010). Often, changes in discharge time series can also be related to changes in climatological time series (Zhang et al., 2014), e.g., for changes in flood type frequencies (Fischer et al., 2019).

Trends and change-points can be generated by different sources: (i) meteorological drivers, such as changes in extreme precipitation patterns; (ii) climatic drivers that can modify soil moisture contents in catchments, such as changes in temperature, annual precipitation or evapotranspiration; (iii) drivers that modify rainfall-runoff processes at the catchment scale, such as changes in land uses; and (iv) stream drivers that modify flood propagation processes, such as river training (Vorogushin et al., 2012). Therefore, time series recorded at catchments that are either natural or near-natural have to be used to identify climate-driven flood trends, avoiding the anthropogenic effects on catchment response. As an example, Bertola et al. (2021) proposes a new framework for attributing flood changes to the potential drivers of extreme precipitation, antecedent soil moisture, and snowmelt, as a function of the return period, in a regional context. Time-series collected by reference hydrological networks can be useful in hydrological change analyses (Burn et al., 2012; Whitfield et al., 2012).

For trend tests, such a relation between statistical results and hydrological evidence is even more important, since often trends are extrapolated into the future (see Iliopoulou and Koutsoyiannis (2020) on the possible issues connected to extrapolating trends). Changes in climate or anthropogenic changes like land-use can be the origin of such trends (Blöschl et al., 2019; Prosdocimi et al., 2015;

Bertola et al., 2021). However, cyclic behavior or so-called flood-rich and flood-poor periods (Lun et al., 2020; Fischer et al., 2023) in the time series can have an impact on the significance of the results (Koutsoyiannis, 2003). Depending on which observation period is considered, trends and change-points can be significant or not (Serinaldi et al. 2018; Kundzewicz et al., 2005). As an example, Figure 3 depicts varying significant linear trends of the mean (continuous colored lines) detected for 30-year time windows of the Annual Maximum discharge Series (AMS) at the Cologne/Rhine gauge (Germany).

Also, the time resolution of the data can have an impact on the results (Mangini et al., 2018). Several trends in hydrological time series all over the world like discharge or precipitation have been detected in recent years but not all of them can be confidently explained with evidence (Madsen et al., 2014). For example, precipitation time series may show a significant increasing trend while the corresponding flood time series do not (see also Sharma et al, 2018). Evidence of deterministic causes must be present for the incorporation of non-stationarities in hydrological models and especially for the extrapolation to the future.

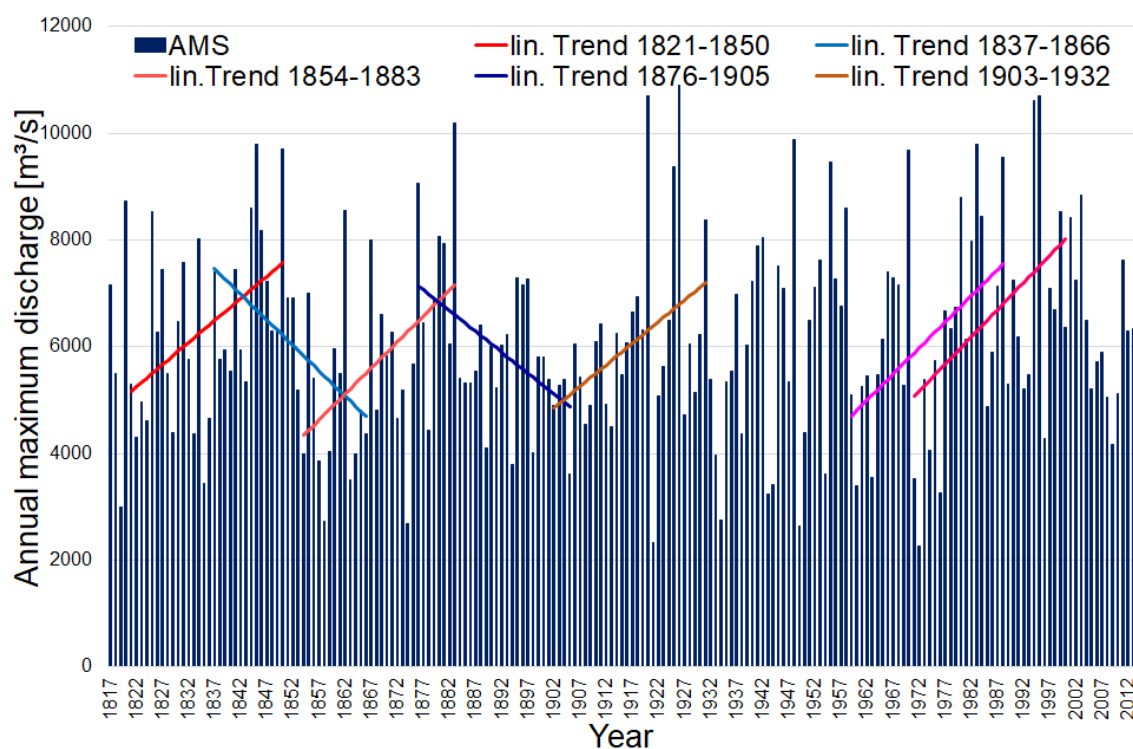


Figure 3 – Example of varying significant trends detected for 30-year time windows of the annual maximum discharge series (AMS) at the Cologne/Rhine gauge; continuous colored lines shows the linear trends of the mean as emerging from the series.

5. Regionalization

The understanding and modeling of hydrological variability in space and the possibility of transferring hydrological knowledge and information from one region/catchment to another are central issues in hydrology for several scientific research areas and operational problems about water resources management and hydroclimatic risk assessment and mitigation; see, e.g., the Predictions in Ungauged Basins (PUB) initiative (Blöschl et al., 2013; Hrachowitz et al., 2013) and Question 5 of 23 UPH (Blöschl et al., 2019).

This Section addresses the state of the art, milestones, and future research avenues in the broad area of statistical regionalization of hydrological information by looking primarily at the prediction of rainfall and streamflow in ungauged locations. In particular, we look at the spatial interpolation of rainfall characteristics and frequency regimes, with a specific focus on rainfall extremes, and regionalization of streamflow regimes and flood frequency, looking primarily at (geo)statistical interpolation and regional frequency analysis. We also consider the related question of streamflow prediction in ungauged locations using rainfall-runoff models with regionalized parameters.

5.1. State of the art

5.1.1. Rainfall regionalization

Precipitation measurements are point observations usually obtained from gauging networks with irregularly distributed sensors in space. If rainfall is needed for ungauged points or areal rainfall is required, like for most hydrological applications, precipitation measurements have to be interpolated in space (e.g. Koutsoyiannis and Langousis, 2011). There are many interpolation methods available, which can be mainly separated into deterministic/geometric approaches and geostatistical techniques. Deterministic approaches like Thiessen Polygons or Inverse Distance Weighting (IDW) are simple and fast, but neither consider the specific spatial persistence behavior of the rainfall nor can they use additional information sufficiently. The geometric spline interpolation is more advanced and can also use additional variables (Hutchinson, 1998a, b). Geostatistical techniques, relying on the concept of random functions providing manifold kriging versions from simple stationary approaches with ordinary kriging over indicator kriging for precipitation occurrence interpolation (Berezowski et al., 2016) to non-stationary (in space) methods like co-kriging (Seo et al., 1990a; Seo et al., 1990b) and external drift kriging, are the state of the art. Especially the latter allows easy incorporation of additional information into the interpolation, like elevation (Goovaerts, 2000), satellite data (Thiemig et al., 2013), or weather radar measurements (Goudenhoofd and Delobbe, 2009; Haberlandt, 2007).

An accurate estimation of extreme rainfall intensities is often needed for the design and assessment of urban infrastructure to minimize potential damage to society. This may be a challenge since records from rainfall gauges are often short and there is a need to also account for the effects of climate change. Only short records are available the estimation of the magnitude of events associated with long return periods is very uncertain. By combining information from different stations, i.e. by trading space for time, regionalization is a possible strategy to reduce the uncertainty in the estimation of design events for locations with short records or even ungauged locations.

Hence, a fundamental component of the process of setting up an interpolation procedure is the assessment of the accuracy of prediction in ungauged locations, which is usually done using cross-validation or split-sampling and enables the user to characterize spatial interpolation errors. Kriging methods are unbiased in space and regarded as standard tools for interpolating point rainfall. However, if time series are interpolated in space for each time step, the accumulated error for

certain points can have a temporal bias, which is significant for hydrological applications (Bárdossy and Pegram, 2013). A simple assessment of uncertainty is provided using estimate and estimation variance when the residuals are normally distributed. If this is not the case indicator approaches or new interpolation methods based on copulas can be used (Bárdossy and Li, 2008).

Regional frequency analysis of hydrological variables is a mature discipline, for which books and manuals exist detailing steps, procedures, statistical tests, and tools for setting up and testing regional models; a classic example is the textbook “Regional frequency analysis: an approach based on L-moments” by Hosking and Wallis (1997). Concerning regional frequency analysis of rainfall extremes, geographic distance and Mean Annual Precipitation (MAP) are generally recommended as similarity measures to be used to pool regional information from gauged sites due to the marked spatial nature of rainfall extremes frequency regime (e.g., Ball et al., 2019) and its significant dependence on climate and orography, which can be effectively summarized by MAP (see e.g. Di Baldassarre et al., 2006; Persiano et al., 2020). Regional frequency analysis of rainstorms may be applied under different approaches, such as regional regression relationships (e.g., Brath et al. 2003), the index-event approach (e.g., Dalrymple, 1960; Hosking and Wallis, 1997; Burn, 2014), or hierarchical regionalization (e.g., Alila 1999), among others. Some countries present official guidelines based on the use of a regional approach for rainfall frequency analysis, such as the Flood Estimation Handbook in the United Kingdom (Institute of Hydrology, 1999). In other countries, the application of local approaches in which only the rainfall records at a given gauge station are used for estimating extreme rainfall events is still a common practice, instead (e.g., see Svensson and Jones 2010, where a review of nationwide rainfall frequency analysis procedures is provided considering nine countries).

The temporal resolution of precipitation matters for the selection of the optimal interpolation method and regarding interpolation performance. Usually, the interpolation error increases with increasing temporal resolution (see e.g. Fig. 1 in Berndt and Haberlandt, 2018), while topography is only of value as additional information for rainfall interpolation if the time steps are larger, becoming significant for data with about weekly aggregation level (Bárdossy and Pegram, 2013; Berndt and Haberlandt, 2018).

Most relevant for short-time step rainfall estimation in space are weather radar data. However, these have usually a large bias (Berne and Krajewski, 2013; Krajewski and Smith, 2002). Merging ground-based point rainfall measurements and radar-derived rainfall can provide corrected rainfall estimates with high resolution in space and time. Over the last years several different merging methods have been applied, like external drift kriging (Goudenhoofd and Delobbe, 2009; Haberlandt, 2007), conditional merging (Berndt et al., 2014; Kim et al., 2008; Sinclair and Pegram, 2005), simple bias correction (Rabiei and Haberlandt, 2015; Thorndahl et al., 2014) and Bayesian approaches (Todini, 2001). An overview and comparison of merging methods especially targeting urban hydrological applications are provided by Ochoa-Rodriguez et al. (2019).

Finally, many recent developments in regional frequency analysis of hydrological variables aim at modeling or detecting climate signals and frequency alterations at a regional scale. Concerning rainfall events, evidence of the effect of climate

change on extreme precipitation is found over the world (e.g., Papalexiou and Montanari 2019; Westra et al. 2014; Persiano et al., 2020; Emmanouil et al., 2022, 2023); hence the need for it to be properly considered when estimating extreme rainfall intensities.

5.1.2. Streamflow regionalization

Analogously to rainfall, an accurate representation of streamflow regime and frequency, from low-flows to floods, is of paramount importance for various water resources planning and management problems that are at the core of the safety and growth of societies. Achieving this objective is hampered by the limited density of stream-gauging networks, which are much sparser than rain-gauging ones even in more advanced countries (see e.g. Parajka et al., 2015), and often subject to a decline in the number of sensors in time due to high maintenance costs. For this reason, since the '60s the hydrological scientific community dedicated huge research attention and efforts to the development of tools and procedures for transferring hydrological information from stream-gauges to ungauged river cross-sections. As summarized for instance in Blöschl et al. (2013; see e.g. chapters 7 and 9), classical approaches adopted for this transfer mainly consisted of statistical hydrological regionalization (see Fig. 4); these originally took the form of (log)linear regression of streamflow, low-flow, or flood quantiles against climate and geomorphological descriptors of gauged river basins, or the index-event approach (or “index-flood approach” when referring to flood flows) mentioned above.

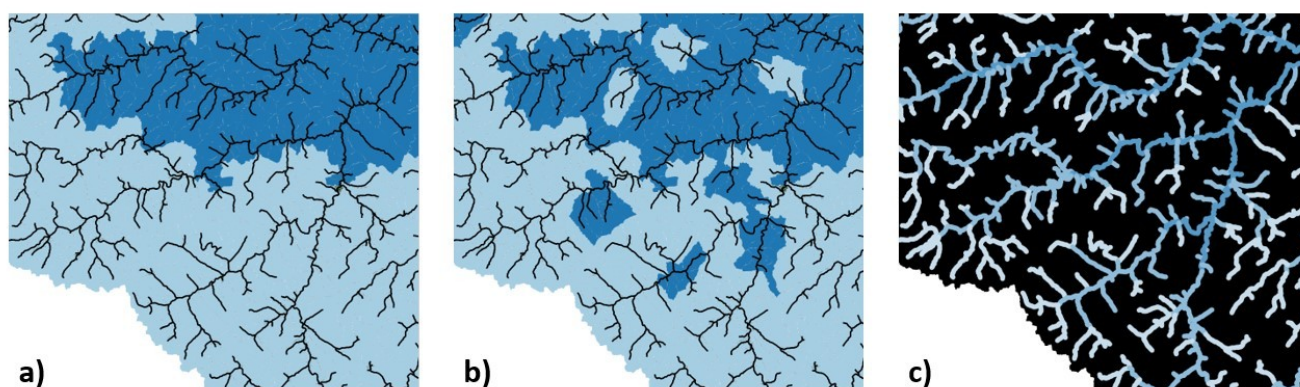


Figure 4 – Spatial support for statistical regionalization: a) classical interpretation (fixed and geographically contiguous homogeneous regions); b) modern interpretation (non-contiguous homogeneous regions, resulting from e.g. cluster analysis of catchment descriptors); c) current interpretation (stream network-based regionalization; typical of focused-pooling, and more recently geostatistical or physiographic space-based interpolation).

Regional flood frequency analysis grew massively as a research topic from the mid-'80s to the revolutionary late '90s and early '00s when the paradigm of focused pooling was introduced (see e.g. Burn, 1990; Reed, 2002). Focused pooling consists of identifying pooling-groups of gauged sites from which to transfer the hydrological information by looking at hydrological similarities with the target site where the regional prediction is needed; hence, the approach dispenses with the delineation of geographically identifiable and hydrologically homogeneous regions (see cases a and b in Fig. 4), a hypothesis at the basis of the classical index-event approach, and adopts flexible pooling-groups of sites that depend on the target site (Ouarda et al., 2001, see Fig.4, case c). A prominent example of focused-pooling is

the so-called Region Of Influence (ROI) approach (Burn, 1990). Focused-pooling (e.g. ROI approach) is generally considered as the baseline regionalization approach and standard practice, to the point that e.g. the ROI approach is used in nationwide guidelines such as the Australian Rainfall and Runoff (ARR) guideline (Ball et al., 2019) and the Flood Estimation Handbook (FEH) in the United Kingdom, as well as in nationwide studies (see e.g. Requena et al. 2019a in Canada). In some other areas, regression-based regional models are indicated as the national reference procedure. Examples are the Guidelines for Determining Flood Flow Frequency (Bulletin 17C) in the US which recommend the Bayesian Generalized-Least-Squares (B-GLS) approach for setting up regional estimation equations (see e.g. Gruber and Stedinger, 2008).

More recently, the paradigm of focused-pooling further evolved into procedures aiming at performing a seamless interpolation of streamflow descriptors (e.g. low-flow indices, flood quantiles, etc.) along stream-networks (see Fig. 4, case c), therefore reproducing the hydrological continuity of streamflow regimes from our fragmented knowledge originating from the sparseness of sensors in stream gauging networks. Examples are methods that regress stream-flow statistics, instead of quantiles, against catchment descriptors (Laio et al., 2011), or methods that contaminate hydrological regionalization principles with statistical interpolation such as kriging (see e.g. Merz and Blöschl, 2005; Farmer, 2016), either performed over the geographical space (geostatistics in the strict sense) or in an n -dimensional space whose coordinates are geomorphological and climatic catchment descriptors, which is also referred to as physiographic-space-based interpolation or canonical kriging in the scientific literature (see e.g., Shu and Ouarda, 2007).

Topological kriging, or Top-kriging, is a prominent example of the first category; similar to a block-kriging in which the support area coincides with the drainage area, Top-kriging was firstly introduced for regionalizing flood-quantiles (see Skoien et al. 2006) and then successfully applied in various hydro-climatic contexts for predicting a broad spectrum of point streamflow indices, such as low-flows (see e.g. Laaha et al., 2014), high flows and floods (Merz et al. 2008), Flow-Duration Curves (FDCs) (Pugliese et al. 2014, 2016; Castellarin et al. 2018), stream temperature (Laaha et al. 2013), habitat suitability indices (Ceola et al. 2018), and daily streamflow series (Skøien and Blöschl 2007, Vormoor et al. 2011, de Lavenne et al. 2016, Farmer 2016). Physiographic space-based interpolation, sometimes also referred to as canonical-correlation (Ouarda et al. 2001), proved to be a rather effective regionalization technique, which can be successfully applied for predicting flood quantiles (Shu and Ouarda, 2007), low-flows (Castiglioni et al., 2011) and FDCs (Castellarin, 2014). Recently, artificial intelligence and Machine Learning-based approaches have been gaining popularity due to the easy availability of computing power (e.g. Ouali et al., 2017, Desai and Ouarda, 2021). These approaches need to be used with care to ensure that the physical concepts and the hydrological phenomena are adequately taken into consideration in the modeling effort.

Additionally, a promising regionalization approach involves the use of panel regression models, a methodology borrowed from the econometrics literature. Panel models represent the relationship between a time series of streamflow at one watershed and a time series of streamflow and/or time series of basin hydroclimatic

characteristics at numerous other sites within a region. In other words, a panel model is a multivariate model of time series specially designed for the types of regional time series problems encountered in hydrology. The economists Croissant and Milla (2008) provide R software for the implementation of panel regressions. Multicollinearity and omitted-variable bias are major limitations to developing multivariate (panel) regression models to estimate streamflow characteristics at ungauged watersheds (Farmer et al., 2015). Since the work of Brown et al. (2011) in documenting the impact of drought on economic growth, panel models have been increasingly used in hydrology for a number of applications. Panel models have been developed to evaluate the effect of urbanization on flood frequency (Blum et al. 2020), the impact of rainfall on low streamflow (Bassiouni et al., 2016), the prediction of groundwater levels (Izady et al., 2012), residential water demand modeling (Worthington et al. 2009), and for determining the impact of urbanization on annual runoff coefficients (Steinschneider et al., 2013).

Another interesting approach for streamflow prediction in ungauged basins through statistical regionalization is the use of rainfall-runoff models with "regionalized" parameter values, which enables continuous simulation. This research area has been investigated using at least two distinct strategies: (i) "direct" regionalization of rainfall-runoff model parameter values, and (ii) "indirect" parameter regionalization through calibration to regionalized flow signatures. The first strategy can be implemented by spatial interpolation of model parameters calibrated at gauged locations (e.g., Merz and Blöschl, 2004; Vogel, 2010; Bárdossy and Li, 2008). Earlier studies estimated rainfall-runoff model parameters at each site followed by attempts to relate model parameters to basin characteristics. The study by Fernandez et al. (2000) implemented both steps concurrently so that the multiple site models are calibrated simultaneously. Simultaneous estimation offers a better chance to reproduce observed streamflow behavior across multiple sites and, importantly, to obtain more stable relationships between rainfall-runoff model parameters and basin characteristics. A significant advance along this research direction was achieved in the study by Samaniego et al. (2010), which developed detailed transfer functions that link catchment attributes to model parameters and calibrated the "hyper-parameters" of these transfer functions at multiple catchments across geographically large areas.

The second strategy, which normally yields smoother parameter variation in space, can be implemented by estimating relationships between flow signatures (e.g., mean and variance of flows, baseflow/flashiness indexes, etc.) and catchment attributes (e.g., catchment slope, geology, etc.). Traditionally, these relationships have been constructed using multi-linear regression techniques (e.g. Yadav et al., 2007) and more recently using Machine Learning techniques such as Random Forests (e.g., Snelder et al. 2013; Addor et al. 2018; Prieto et al. 2019). The identification of rainfall-runoff model structure under ungauged conditions and its impact on streamflow estimation has also received attention (Prieto et al., 2022). Regardless of the strategy, obvious challenges persist in terms of establishing spatial relationships for the pertinent quantities – which are essentially the same as the challenges in establishing spatial relationships in flood frequency analysis.

More recently, the main objective of regional frequency analysis may be properly accounting for non-stationarities and changes of frequency regimes at the regional scale (see e.g. Cunderlik and Burn, 2003; Leclerc and Ouara, 2007; Bertola et al.,

2020), which may imply using detected alterations and trends to form hydrologically similar regions (O'Brien and Burn, 2014). Alternatively, a few studies aim at improving the robustness and reliability of trend detection in annual flood sequences by testing for trends at a regional scale (Kjeldsen and Prosdocimi, 2021). Some non-stationary regional flood frequency analysis techniques proposed in the literature have been recently compared to each other, yet the body of studies in this area is still very limited and worth expanding soon (Kalai et al., 2020).

Together with textbooks and guidelines, several packages for implementing and testing regional statistical models, including geostatistical interpolation models such as Top-kriging, have been developed under the free and open-source software R (R Core Team 2020). Table 4 reports some R packages developed and maintained by ICSH-STAHY members.

Table 4 – Package for regionalization analysis and modeling

Name	Brief description	Repo.	Link	Authors
floodnetRfa	Package implementing FloodNet recommendations for flood frequency analysis	GitHub	https://github.com/floodnetProject16/floodnetRfa	M. Durocher, E. Ansell, and the FloodNet project
geoFDC	Non-supervised and geostatistically interpolated regional FDCs	GitHub	https://github.com/alessio-pugliese/geoFDC	A. Pugliese
lmomRFA	Functions for regional frequency analysis using the methods of Hosking and Wallis (1997)	CRAN	https://cran.r-project.org/web/packages/lmomRFA/index.html	J.R.M. Hosking
ncdf4	Interface to Unidata netCDF (Version 4 or Earlier) Format Data Files	CRAN	https://cran.r-project.org/web/packages/ncdf4/index.html	D. Pierce
nsRFA	A collection of statistical tools for objective (non-supervised) applications of the Regional Frequency Analysis methods in hydrology	CRAN	https://cran.r-project.org/web/packages/nsRFA/index.html	A. Viglione et al.
pREC	Package for quantifying regional information content for cross-correlated annual sequences, useful for assigning a frequency to regional envelope curves	GitHub	https://github.com/alessio-pugliese/pREC	A. Pugliese
RMWSPy	Python package for conditional spatial random field simulation and inverse modeling which can be	GitHub	https://github.com/SebastianHoern	s. Hörning and B. Haese

	used to simulate rainfall fields conditioned on commercial microwave link data		ing/RMWSPy	
Rtop	Geostatistical interpolation of data with irregular spatial support such as runoff related data or data from administrative units (TopKriging)	CRAN	https://cran.r-project.org/web/packages/rtop/index.html	J.O. Skøien
TNDTK	Repository containing an application example for extracting period-of-record (FDCs) from daily streamflow series observed at gauged sites and computing FDCs at ungauged target sites using total negative deviation Top-kriging	GitHub	https://github.com/SimonePersiano/TNDTK/tree/v1.0.0	S. Persiano et al.
winfapReader	Interact with Peak Flow Data in the United Kingdom	CRAN	https://cran.r-project.org/web/packages/winfapReader/index.html	I. Prosdocimi
WREG	Develops regional estimation equations for streamflow characteristics that can be applied at ungauged basins (approaches allowed: ordinary-least-squares, OLS; weighted-least-squares, WLS; and generalized-least-squares, GLS)	GitHub	https://github.com/USGS-R/WREG	W. Farmer and USGS Team
statsmodels	Python module that provides classes and functions for the estimation of many different statistical models, as well as for conducting statistical tests, and statistical data exploration	statsmodels.org	https://www.statsmodels.org/stable/index.html	Seabold and Perktold, 2010
scipy.stats	Python module that contains a large number of probability distributions, summary and frequency statistics, correlation functions and statistical tests, masked statistics, kernel density estimation, quasi-Monte Carlo functionality, and more	scipy.org	https://docs.scipy.org/doc/scipy/reference/stats.html	Virtanen et al.
pyMannKendall	Python package for non-parametric Mann-Kendall family of trend tests	pypi.org	https://pypi.org/project/pymannkendall/#description	Md. Manjurul Hussain and Ishtiak Mahmud, 2019
pyHomogeneity	Python package for Homogeneity Test	pypi.org	https://pypi.org/project/pyhomogeneity/#description	Md. Manjurul Hussain, Ishtiak Mahmud

				and Sheikh Hefzul Bari, 2020
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5.2. Challenges and open problems in regionalization

Geostatistical interpolation of point information produces a smoothed continuous representation of the point variable of interest in space (e.g. interpolation of point rainfall via ordinary kriging, but also interpolation of a given streamflow-index via Top-kriging or physiographic-space-based interpolation). One of the main disadvantages of this procedure is the loss of variance, i.e. the underestimation of high values and the overestimation of low values (see e.g. Castellarin, 2014). The preservation of the variance should be considered when evaluating interpolation methods (Berndt et al., 2014). Usually, the assimilation of additional information, especially information deriving from weather radars for point rainfall, may improve the representation of the actual variance of the process. A noteworthy approach is the “maintenance of variance extension methods” (MOVE) introduced by Hirsch (1982). MOVE methods have been applied to rainfall, streamflow, and many other hydrologic records and extensions were developed to ensure that they perform as expected under either augmentation or extension (Vogel and Stedinger, 1984). Augmentation refers to the estimation of moments of hydrologic records at short record sites by transferring information from nearby longer record sites. Extension refers to filling in the observations at the short record site using the longer record site. MOVE methods are in common use by the U.S. Geological Survey as evidenced by their inclusion in the USGS R package already mentioned in Table 1. More recently, conditional simulation methods have been introduced to preserve the variance and provide uncertainty estimation (AghaKouchak et al., 2010; Hörning and Bárdossy, 2018; Seo et al., 2014). It is relevant to mention also the patched-kriging approach proposed by Libertino et al. (2018), dealing with the loss of variance due to spatial interpolation of point maxima. Notwithstanding these advancements, the preservation of variance represents an interesting open problem for future analyses (see also Farmer and Vogel, 2016). The relatively sparse precipitation networks very likely miss the true extremes of an event. This causes a serious problem for estimating point and areal extremes.

The quality of regionalization is often measured with correlation, Nash-Sutcliffe efficiency, or other similar measures; the reader is referred to Barber et al. (2020), Clark et al. (2021) and Lamontagne et al. (2020) for a discussion on the variability of such measures when computed from daily streamflow. Unfortunately, in the case of a strong annual cycle, these numbers often indicate a much higher skill. Therefore, well-known annual cycles should be removed before the evaluation.

Focusing more specifically on point rainfall, it has to be noted that precipitation is a space-time dynamic process, which is an issue also for multisite rainfall generation (Section 4.2.2). Therefore, a pure spatial interpolation is not optimal, as it does not consider the advection of rainfall fields and their temporal persistence, which can be especially relevant for a short-duration event. Special interpolation methods, which can account for this space-time behavior, might improve the performance of rainfall interpolation (Fitzner and Sester, 2015). Also, the interpolation of distribution functions, honoring the spatio-temporal aspects might improve the

interpolation performance (Lebreznz and Bárdossy, 2019) and it is, therefore, worth investigating further. Another important problem is the large portion of zero rainfall. The number of dry stations increases with finer spatial resolution. This affects both the assessment of spatial variability and spatial/space-time interpolation.

Although it has been shown that blending weather radar data with raingauge observations generally results in smaller interpolation errors relative to using either data separately, the use of the data merger e.g. as input for hydrological modeling is not standard practice yet (Berne and Krajewski, 2013). This might be due to the complexity of developing the merger products, or too little confidence in radar data products, but also to the specific result of specific scientific research projects (Price et al., 2014; Zhu et al., 2014). Research initiatives could advance our knowledge, providing valuable information for practical applications, including recent research activities considering the potential of alternative data sources to be used for spatial interpolation of rainfall, such as crowdsourced information (de Voss et al., 2019; Bárdossy et al., 2021; Haberlandt and Sester, 2010) or data on the attenuation of electromagnetic signals in commercial microwave links (see e.g. Haese et al., 2017) or recordings of video cameras (Allamano et al. 2015). The combination of these alternative data sources with conventional raingauges shows great potential for improving the spatial interpolation of rainfall data and offers interesting opportunities for future research on merging techniques.

While, as noted above, the spatial interpolation of point rainfall may significantly benefit from information on spatial correlation of rainfall fields gathered by weather radar data (or commercial microwave links), we are currently lacking reliable information sources for improving our representation and modeling of spatial correlation (also termed as intersite correlation, or cross-correlation) for regional frequency analyses of hydrological variables, and particularly so for extreme events such as rainstorms, floods, low-flows.

Intersite correlation is a valuable indicator of hydrological similarity that can be effectively exploited in regional flood frequency analysis (see e.g. Archfield and Vogel, 2010), and that is directly modelled and used by Top-kriging and GLS for producing regional prediction of the hydrological variable of interest. Nevertheless, the effects of intersite correlation are also to be better understood and quantified as they control the actual information content of a regional sample (see e.g. Castellarin, 2007 and references therein), and consequently the uncertainty and accuracy of regional predictions (Guo et al., 2021), they also impact statistical tests for assessing the regional homogeneity of a pooling group of sites (Castellarin et al., 2008; Lilienthal et al., 2018). Improving our understanding and representation of intersite cross-correlation is one of the key elements for enhancing the accuracy of regional estimates, bringing regional estimators closer to the unknown true theoretical values (Persiano et al., 2021).

Another serious problem is that precipitation and discharge are usually regionalized independently, which very often leads to inconsistent datasets (Kauffeldt et al. 2013). Therefore, methods to regionalize dependent variables simultaneously are required. Attempts to do so can be found in Grundmann et al. (2019) and Bárdossy et al. (2021).

The choice of distribution of the extreme values is a key decision in most regionalization studies. In the stationary case, most studies and procedures rely on well-known 2-4 parameter models such as the LP3, GEV or Kappa distributions (see e.g. Hosking and Wallis, 1997). Regionalization of, in particular, the shape parameter is often challenging due to a combination of high sampling variance of the third-order moment and the generally weak link to existing catchment descriptors (e.g. Lun et al., 2021). Another challenge is the need to select appropriate model structures when moving from stationary to non-stationary models. For example, Prosdocimi and Kjeldsen (2021) showed that extrapolation from popular non-stationary models can result in counter intuitive estimates of future design floods when the location parameter is changing while the scale parameter is kept constant. Instead, they proposed a re-parametrized non-stationary version of the GEV model which preserves a constant CV and thus ensures credible extrapolations. The challenge of selecting and regionalizing non-stationary models needs to be considered carefully to ensure the operational value of these models.

Finally, and more specifically on non-stationarity, quoting Faulkner et al. (2020), can we still predict the future from the past? Or equivalently, in the face of global environmental change (see Visessri and McIntyre, 2016) is "trading space for time" still a reliable and viable working hypothesis? These are still very relevant and fundamental research questions to the PUB problem in the field of regional frequency analysis of hydrological variables. Our ever-growing computational capabilities combined with currently available cloud-computing possibilities and steadily increasing open accessibility to high-resolution global-coverage datasets seem to indicate regionalization of hydrological models (Guo et al., 2021) and continuous rainfall-runoff simulation as a promising way forward, one which is worth investing research efforts and resources. In this context, regional modeling of extreme rainfall events, in terms of magnitude, spatial distribution, and frequency, as well as future climate scenarios, assume pivotal importance.

Concerning frequency analysis of rainfall extremes, further efforts could be dedicated to promoting the use of regional approaches for practical application. A global comparative assessment of the performance of regional rainfall approaches, in a similar way to that carried out for floods and low-flows by Salinas et al. (2013), would be beneficial for providing general recommendations. Regarding future climate scenarios, and focusing in particular on climate model simulations used and frequency analysis for estimating regional and continental future hydrological extreme events, global initiatives such as the Coordinated Regional Climate Downscaling Experiment (CORDEX, <https://cordex.org>) are currently in progress; they aim at gathering regional climate downscaled simulations from many climate models under similar scenarios, projections, resolutions, time scales and periods for facilitating their use in practice. Considering the wide variety of approaches to be used for estimating future extreme rainfall, some studies attempt to provide recommendations but the literature is still sparse. For instance, bias correction of climate model simulations for their use in extreme rainfall estimation is recommended to be applied to annual maxima under a regional approach (Li et al., 2017), using simulations and observations with a similar spatial and temporal resolution (Maraun, 2013). So far, only a few studies deal with the estimation of future extreme rainfall by accounting for a regional approach (e.g., DeGaetano and

Castellano, 2017; Ekström et al., 2005; Li et al., 2017; Requena et al., 2019). Due to the large uncertainty involved in future extreme rainfall estimation (e.g., uncertainty in climate model simulations, spatial and temporal downscaling methods, re-gridding method, and bias correction methods, among others), the recurring general recommendation consists in considering as many methods as possible, and therefore this issue is still wide open for future research contributions.

6. Conclusions

In this paper, we provide a summary of the collaborative activities undertaken within the STAHY-WG (Statistical Hydrology Working Group) and later the ICSH (International Commission on Statistical Hydrology) of IAHS (International Association of Hydrological Sciences). The multidisciplinary nature of this community encompasses various research fields. However, in this paper, we specifically concentrate on four areas that have garnered significant attention over the past fifteen years and we discuss open problems and challenges that still persist within the domains of extreme value analysis, multivariate frequency analysis, time series analysis and simulation, and regionalization.

Regarding extreme value analysis, besides extensively studying the appropriate distributions such as the common GEV and GP functions, a recent promising development has emerged. It pertains to the potential to relax the constraint of the independence condition (i.e., metastatistical distribution), which would enable simplifying the frequency analysis and expanding and optimizing the available sample size. However, the issue of non-stationarity remains an unresolved challenge, despite considerable efforts devoted to its investigation. It needs to be adequately and comprehensively addressed in a general context.

Multivariate analysis, particularly involving the copula function, has gained recognition as a best practice. At the outset of the collaborative endeavors between STAHY-WG and the ICSH commission, the copula function was just introduced in hydrology. While it showed great potential, there were several drawbacks in the inference procedure and limitations in its applications. However, through intensive activities such as short courses and workshops, significant progress has been made. The entire procedure has been reviewed, improved, and solidified, enhancing its applicability in hydrology. Currently, the multivariate inference procedure is well-established, similar to the univariate case. This contribution emphasizes certain considerations, such as the importance of conducting preliminary analysis, carefully considering sample size, and exploring the full range of available copula functions. Looking ahead, a future challenge lies in eliminating the requirement of marginal autocorrelation, in alignment with the univariate case.

On the topic of time series analysis, in addition to strengthening established procedures for streamflow simulation, a substantial effort has been dedicated to rainfall simulation models, which are crucial for various hydrological analyses. One notable challenge is the existence of multiple approaches with different theoretical backgrounds, which can be confusing for practitioners. We acknowledge that it is impractical to identify a single best rainfall simulation model suitable for all applications. Therefore, the future challenge lies in two aspects. First, it involves establishing a proper classification system that links the different models to their specific applications. This would aid practitioners in selecting the most appropriate

model for their needs. Second, there is a need to enhance the technological transfer process, making the rainfall simulation models more user-friendly for the end-users. By addressing these challenges, we can improve the accessibility and usability of rainfall simulation models, benefiting the broader community of users.

Regarding the regional estimation techniques, there is a pressing need to consider the multivariate nature of the hydroclimatic variables under study (e.g., floods, low-flows, extreme rainfall events, droughts). This requires viewing them as intertwined elements of a single and complex unicum, and by correctly representing their relationships and mutual constraints.

Undoubtedly, this contribution provides only a limited overview, acknowledging that numerous other intriguing and critical topics in statistical hydrology warrant similar analysis. This review aims to guide and support the future STAHY community in identifying the next research challenges in statistical hydrology, a field currently undergoing a revival driven in part by the rise of machine learning, big data, and artificial intelligence in hydrology. These are all sub-fields of, or heavily reliant on, the fundamental methods of statistical hydrology (as pointed out by R.M. Vogel in his review of this paper). Therefore, the interpretation of who should be part of the future STAHY community should be as broad and inclusive as possible.

Additionally, the ICSH Commission recognizes the importance of stimulating the hydrological community to contribute solutions through the application of statistical hydrology tools. This aligns with the overarching goal of the IAHS to advance the field of hydrology and address key challenges through the HELPING-Science for Solution initiative in the coming decade. By embracing new technological advancements and fostering collaboration between data science and statistical methods, the hydrologic community can strive towards innovative solutions and make significant progress in addressing complex water-related issues.

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