A methodology to estimate flow duration curves at partially ungauged basins

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Abstract. The Flow Duration Curve (FDC) set up at a specific site has a key role to the knowledge of the streamflow characteristic at that site. The FDC gives information on the water regime providing information to optimally manage the water resources of the river. Spite of its importance, because of the lack of streamflow gauging stations, the FDC construction can be a not straightforward task. In partially gauged catchments, FDCs are usually built using regionalization methods among the others. In this paper we show that the FDC is not a characteristic of the basin only, but of both the basin and the weather. Different weather conditions lead to different FDC for the same catchment. The differences can often be significant. Similarly, the FDC built at a site for a specific period cannot be used to retrieve the FDC at a different site for the same time window. In this paper, we propose a new methodology to estimate FDCs at partially gauged basins (i.e., target sites) using discharge and precipitation data gauged at another catchment (i.e., donor catchment). The main idea is that it is possible to retrieve the FDC of a target period of time using the data gauged during a given donor time period for which data are available at both target and donor sites. To test the methodology, several donor and target time periods are analyzed and results are shown for two different case study areas. The comparison between estimated and actually observed FDCs show the reasonability of the approach especially for intermediate percentiles.

1 Introduction

A duration curve is a function that associates to a specific variable its exceedance frequency. Specifically, in hydrology a Flow Duration Curve (FDC) is a function describing the flow variability at a specific site during a period of interest. It represents the streamflow values, gauged at a site, against their relative exceedance frequency. An empirical long-term FDC is the complement of the empirical cumulative distribution function of streamflow values at a given time resolution based on the complete streamflow record available for the basin of interest (Castellarin et al., 2007). FDCs are built as explained in the followings:

– rank the streamflow values in descending order;

– plot the sorted values against their corresponding frequency of exceedance.

The duration d_i of the *i-th* sorted observation is its exceedance probability P_i. If P_i is estimated using a Weibull plotting position (Weibull, 1939), the duration d_i for any q_i (with $i = 1;\ldots;N$) is

$$d_i = P(Q < q_i) = P_i = \frac{i}{N+1}, \tag{1}$$

where N is the length of the streamflow series and q_i is the *i-th* sorted streamflow value.

The FDC provides historical information on the water regime: on the severity of the droughts and on the magnitude of high flows. Several time resolutions of streamflow data can be used to build the FDC: annual, monthly or daily. However, the finer is the resolution, the higher is the information provided by the FDC about the hydrological characteristics of the river (Smakhtin, 2001). FDCs may be built either on the basis of the whole available record period (Vogel, 1994); or on the basis of all similar months (Smakhtin et al., 1997); or on the basis of a specific month.

In one curve, the FDC condenses a wealth of hydrologic information that can be easily accessed. Because of the key role of runoff variability to both water resources management and environmental health maintenance, FDC is used in a large variety of applications as reported by Vogel (1994). For instance, FDC can quantify the capacity of the river to meet intake request as it provides information about the reliability of the water resource for water abstraction activities (Dingman, 1981). It is at the base of hydropower plants design as they are used to determine the hydropower energy potential, especially for run-of-river plants (Hänggi and Weingartner, 2012; Blöschl et al., 2013). As FDC is a key signature of runoff variability, it can be used to assess the impact of changes in a catchment. To this end, through the FDC, Vogel et al. (2007) introduced the indicators of the eco-deficit and eco-surplus. Moreover, the FDC can be used to define and investigate low flows (Smakhtin, 2001). The knowledge of the streamflow characteristics is also relevant for stream water quality studies, for instance, to regulate the proper threshold for chemical concentration and load (Bonta and Cleland, 2003). FDC has a further application in model calibration. This application is based on the replication of the flow frequency distribution rather than of the simulation of the hydrograph (Yu and Yang, 2000; Westerberg et al., 2011). Other applications are related to irrigation planning (Chow, 1964); schedule optimal flow release from reservoirs (Alaouze, 1991); basins afforestation (Scott et al., 2000); investigation of the effects on flows regime due to catchments vegetation change (Brown et al., 2005).

Spite of FDC importance, FDC is affected by the lack of data in ungauged and poorly gauged basins. Many authors dealt with the issue of FDC prediction at ungauged or partially gauged locations through regional regression (e.g., Fennessey and Vogel, 1990; Mohamoud, 2008; Rianna et al., 2011, 2013; Castellarin et al., 2013; Pugliese et al., 2016) and geostatistical interpolation (e.g., Pugliese et al., 2014). Ganora et al. (2009) developed a methodology to estimate FDC at ungauged sites based on distance measures that can be related to the catchment and the climatic characteristics. Hughes and Smakhtin (1996) proposed a method to extend and/or filling in daily flow time series at a site using monthly FDCs of the target site itself. These monthly FDCs should be recorded during a donor period or retrieved using different methods such as (i) regionalization of FDCs based on available observed records from several adjacent gauges (Smakhtin et al., 1997) or (ii) conversion of FDCs calculated from monthly data into 1-day FDCs (Smakhtin, 1999). Since the main limitation of the approach proposed by Hughes and Smakhtin (1996) is that it is based entirely on observed flow records, later, Smakhtin and Masse (2000) proposed a further development, which uses the current precipitation index (CPI) of the donor site to extend the daily hydrograph at the target site. The major assumption is that both the CPIs occurring at donor sites in a reasonably close proximity to the target site and target site's flows themselves correspond to similar percentage points on their respective duration curves. On the other hand, the basic assumption of the spatial interpolation algorithm proposed by Hughes and Smakhtin (1996) is that flows occurring simultaneously at sites in reasonably close proximity to each other correspond to similar probabilities on their respective flow duration curves. On the contrary, one important message of our paper is that FDCs can be very different from time period to time period both at the site itself and at pairs of sites as a long term change in the weather effects the FDCs. Therefore, our approach is based on the concept that proximal sites do not share similar FDCs. This will be demonstrated in the paper applying a two-sample Kolmogorov-Smirnov test to pairs of stations. The usual assumption that they and the related indices are characteristic for the catchment is not true. Therefore, the FDCs built at a given location for different periods cannot be regarded as the same distribution. It is not possible to determine a unique distribution and therefore a unique set of parameters. The same results from the analysis of FDCs built in two different catchments. It is not possible to develop relations between parameters of the basin and characteristics of the FDC to yield synthesized FDCs in locations where flow data are not available, as done for instance by Quimpo et al. (1983). These issues have a key role especially when dealing with ungauged basins.

The main idea underlying our work is to build the FDC at a target site using a filter, which relates the distributions of the discharge and the precipitation. As the weather is the main driver of annual runoff variability, we propose a transformation driven by the weather. The paper is organized as follows. First, the case studies are presented and catchments are grouped into energy- and water-limited ones. Then, the Kolmogorov-Smirnov test is carried out on pairs of FDCs to assess whether these curves can be regarded as the same distribution. Second, the methodology is presented and applied to a set of catchments located in Germany and in U.S. Finally, results are shown and discussed.

2 Case study area

The methodology was applied to several catchments located in two different areas. Ten basins are located in the upper Neckar River basin (Germany), while ten basins are located on the Gulf coast of the USA. In the followings, the two case study areas are presented. Since the procedure is based on the climatological characteristics of basins, catchments will be divided in water and energy limited ones.

2.1 Upper Neckar catchments (Germany)

This study uses data from ten sub-catchments belonging to the Upper Neckar River basin, south-west Germany. The Neckar is a tributary of the Rhine, it springs at an altitude of 706 m a.s.l. and it is 367 km long, Figure 1. The Upper Neckar catchment lies in between the Black Forest and Schwäbische Alb in the Baden-Württemberg region. The basin has an area of 4000 km^2, its elevation ranges from about 240 m a.s.l. to around 1010 m a.s.l., with a mean elevation of 548 m a.s.l. (Singh et al., 2012). The sub-catchments are characterized by a drainage area ranging from around 120 km^2 to about 4000 km^2. The region is characterized by warm summers and mild winters (Samaniego, 2003). In the Upper Neckar catchments, the main geological formations originated in the Triassic and Jurassic periods. The main formations are composed of altered keuper, claystone-jura, claystone-keuper, limestone-jura, loess, sandstone and shelly limestone (Muschelkalk), Samaniego (2003). The effect of soil type can strongly modify the impact of climate on the water balance. For instance, karstic and non-karstic catchments are characterized by very different water balances, since an underground karstic catchment is very different from its overground catchment. The presence of karstic regions makes difficult the transfer of information from precipitation to discharge data in the same basin and from a karstic basin to a not karstic one. Approximately 35% of the basin has karstic formations (Samaniego et al., 2010).

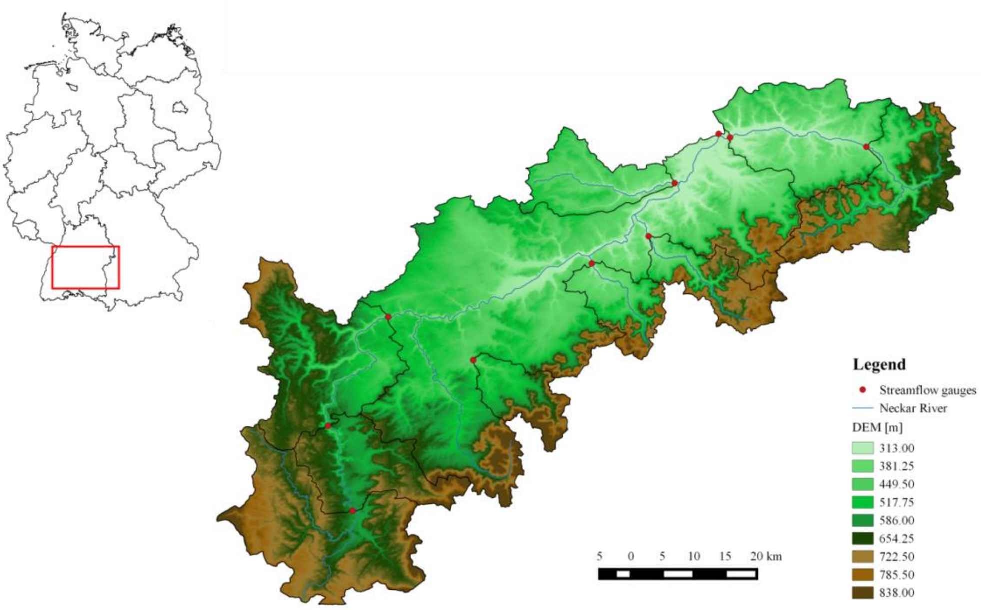

Figure 1. Streamflow gauges (red circles) used to test the methodology in the corresponding catchments located on the Upper Neckar River, Germany.

The mean daily discharge, precipitation, and evapotranspiration, the minimum and maximum daily temperature are available for each sub-catchment for the period 1961-1990. Basins characteristics are presented in Table 1; for more details on this study area, please refer to Samaniego (2003) and Bárdossy et al. (2005). Snow effects are considered by a simple snow accumulation and snowmelt model using a degree day approach. This allows to convert snow to a daily liquid.

Table 1. Study area: upper Neckar catchments in south-west Germany

Catchment	Area	Drainage area	Elevation	Slope	Annual discharge	Annual precipitation
	km^2	km^2	m	degree	mm	mm
Rottweil	456	456	555–1010	0–34.2	352.7	976
Obendorf	235	691	460–1004	0–44.2	360.5	953
Horb	427	1118	383–841	0–48.9	417.5	1158
Rangendingen, Starzel	118	118	421–954	0–36.9	347.4	905
Wannweil, Echaz	135	135	309–862	0–45.9	654.1	877
Riederich, Erms	170	170	317–865	0–49.4	556.5	956
Oberensingen, Aich	175	175	278–601	0–27.1	234.3	762
Suessen, Fils	340	340	360–860	0–49.3	547.2	1003
Plochingen, Fils	352	692	252–785	0–39.7	446.6	936
Plochingen, Neckar	473	3962	241–871	0–45.8	397.2	863

2.2 USA catchments

The catchments on the Gulf coast of the USA are located in three different States: Florida, Louisiana and Texas, Figure 2. These basins were selected because they are characterized by a mild climate and therefore, no snow events have been recorded, allowing us to neglect the snow melting effect. Daily streamflow discharge and precipitation values are available for each catchment for different time windows, Table 2.

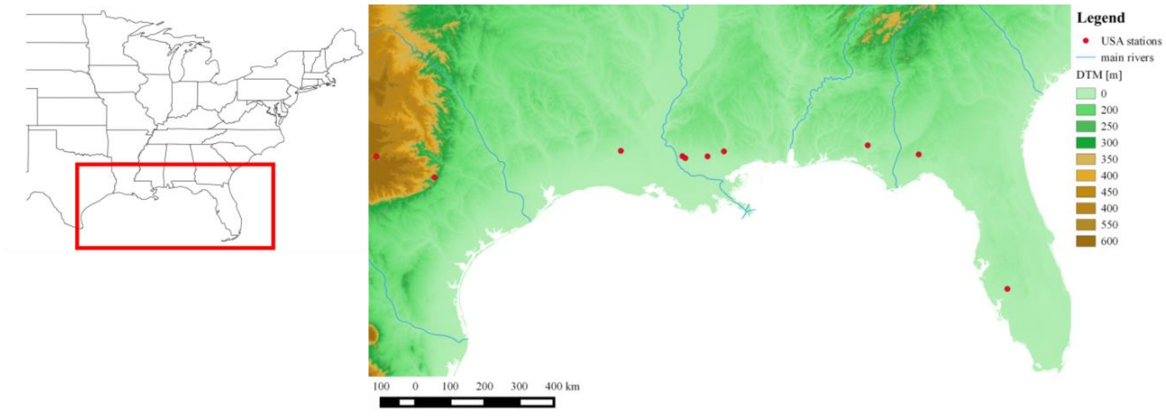

Figure 2. Streamflow gauges (red circles) used to test the methodology in the corresponding USA catchments.

Daily streamflow discharge data were originally provided by the United States Geological Survey (USGS) gauges, while mean areal precipitation and climatic potential evaporation were supplied by the National Climate Data Center (NCDC) at daily resolution. The data set is a subset of the Model Parameter Estimation Experiment (MOPEX) database, used for hydrological model comparison studies (Duan et al., 2006) and for simultaneous calibration of hydrological models (Bárdossy et al., 2016).

Table 2. US case study area: streamflow gauges and corresponding catchments characteristics

Station name	Drainage Area *km*^{2}	Mean elevation *m*	Mean slope -	Mean discharge *mm*	Mean annual precipitation *mm*	Available record -
Peace River At Arcadia, FL	3540.53	32.3	0.3	257.4	1296.2	1948-2001
Ochlockonee River Nr Havana, FL	2952.6	75.6	1.8	322.6	1366.7	1948-2001
Choctawhatchee River at Caryville, FL	9062.41	92.2	3.2	540.8	1464.7	1948-1994
Bogue Chitto River near Bush, LA	3141.67	101.6	1.8	579.2	1637.1	1948-1999
Tangipahoa River at Robert, LA	1673.14	76.9	1.6	635.2	1682	1948-1999
Comite River near Comite, LA	735.56	59.6	1.1	595.9	1644.2	1948-1999
Amite River near Denham Springs, LA	3315.2	75.6	1.3	584.1	1647.9	1948-1999

Calcasieu River near Oberlin, LA	1950.27	62.2	1.1	502.9	1558.9	1948-1986
Llano Rv near Junction, TX	4807.04	670.9	3.4	34.8	645.8	1948-1988
Blanco Rv at Wimberley, TX	919.45	417.3	5.2	140.6	896.7	1948-2001

2.3 Energy and water limited catchments

Annual runoff variability is driven by the relative availability of water (i.e., precipitation) and energy (i.e., evaporation potential). Therefore, the weather is the most important driver of annual variability (Blöschl et al., 2013). Much of the annual runoff variability can be explained observing the different availability of water and energy. For instance, if more water arrives to the catchment than energy can remove through evaporation, the annual runoff will be high. Moreover, in this case the relationship between runoff and precipitation will be more linear than when more energy is available to evaporate the water. On the other hand, in an arid region, the aridity of the climate determines a high inter-annual runoff variability because of the non-linear relationship between runoff and precipitation. Therefore, differences in water and energy availability cause differences in annual runoff variability. However, additional factors such as differences in seasonality and precipitation must be considered (Jothityangkoonad and Sivapalan, 2009). The relative availability of water and energy can be described through the Budyko curve (Budyko, 1974). The curve plots the ratio between mean annual actual evaporation and mean annual precipitation as a function of the ratio between mean annual potential evaporation and mean annual precipitation (i.e., the aridity index). Therefore, it defines a similarity index (i.e., the aridity index) to express the availability of water and energy, and thus bolsters the classification of hydrological sceneries into various degree of aridity. The Budyko curve represents the effects of water and energy availability on annual runoff variability. Moreover, it provides indication about the synchrony of evaporation and precipitation. For instance, where precipitation and evaporation are in phase, runoff production reduces since the catchment infiltrates and stores water and vice versa. Many regions range from in phase to out of phase because of the strong seasonality of climate forcing. However, also the climatic timing can influence runoff variability as presented by Montanari et al. (2006). They shown that the difference in annual runoff between two years with equivalent annual precipitation was of 100% in a monsoonal area of Northern Australia because during the wet year the precipitation occurred during the wet season, i.e., when the potential evaporation was smaller. In this framework, it is important to understand the behavior of the catchments under analysis. To this end, we analyzed the mean annual runoff coefficient, the annual precipitation and the annual evapotranspiration against the annual mean temperature. This analysis is essential to understand the causal processes leading to the long-term mean and variability of runoff as also described in McMahon et al. (2013). The mean annual runoff coefficient is defined as:

$$\mu_R = \frac{\overline{Q_{yr}}}{\overline{P_{yr}}}, \tag{2}$$

where $\overline{Q_{yr}}$ is the annual discharge volume and $\overline{P_{yr}}$ is the annual precipitation volume.

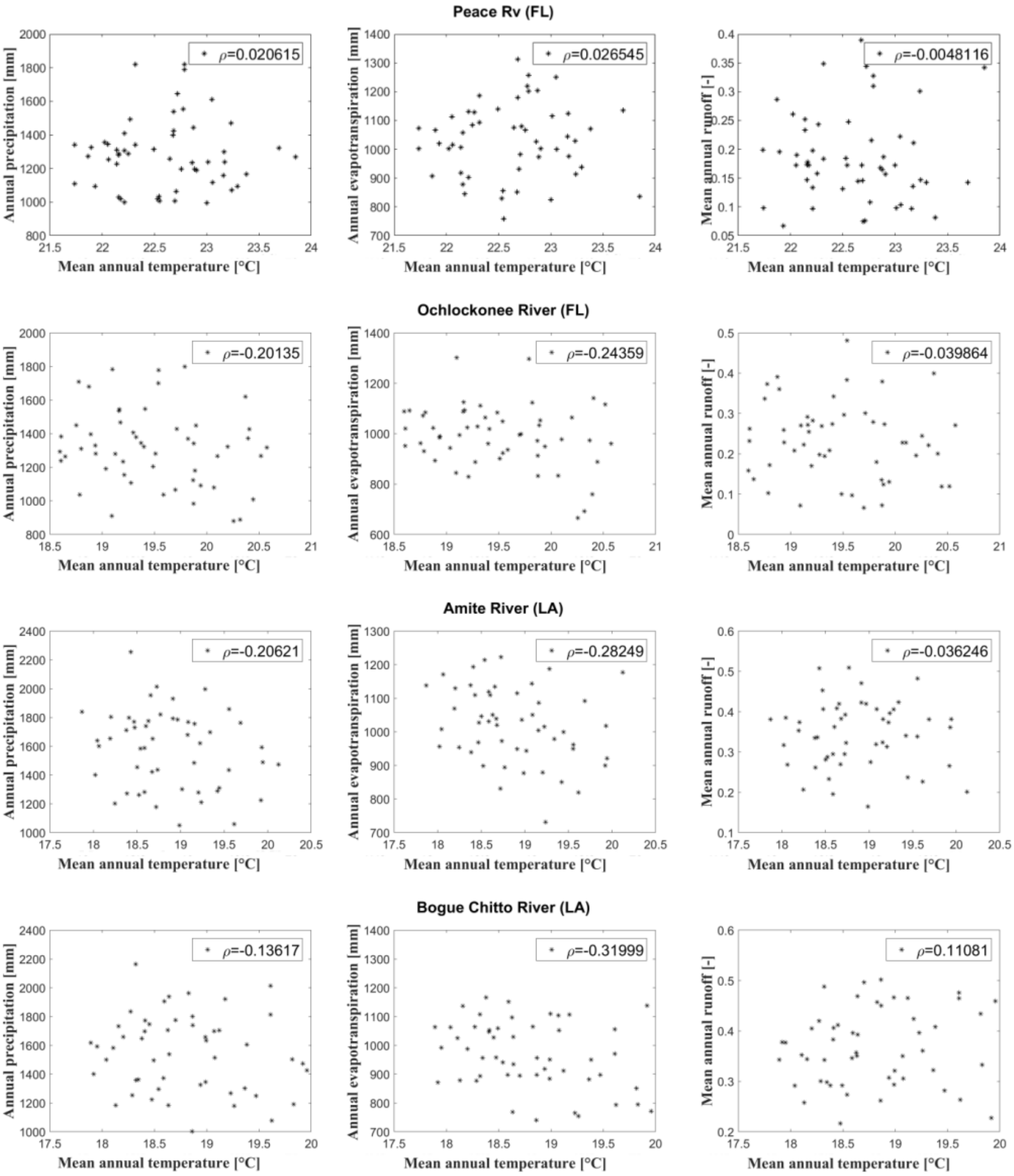

Figure 3. Annual precipitation against mean annual temperature (left panel), annual evapotranspiration against mean annual temperature (middle panel) and annual runoff coefficient against mean annual temperature (right panel) for four different catchments: Peace River (FL), Ochlockonee River (FL), Amite River near Denham Springs (LA), Bogue Chitto River (LA). In each plot, the Pearson correlation coefficient ρ is reported in box.

Results show that catchments have two different behaviors: precipitation, evapotranspiration and runoff have either a positive or a negative correlation with the air temperature. In the former case the evapotranspiration is limited by the available water, which happens in water-limited catchments; in the latter the evapotranspiration is limited by the available energy which happens in energy-limited catchments. For instance, measurements at Peace River (LA) suggest that the catchment is balanced between energy and water limitation by the correlation criterion, Figure 3 upper panel. While Ochlockonee River (FL), Amite River near Denham Springs (LA) and Bogue Chitto River (LA) are energy-limited. Results for Amite River are consistent with what found by Carrillo et al. (2011). Since it is not possible to infer discharge values of a water-limited catchment from the data set of an energy-limited one, analysis have been carried out on climatically homogeneous sets of basins.

2.4 Preliminary analysis

The FDC can be interpreted as a distribution function of discharge over a given time period. To determine if samples are drawn from the same distribution, the two-sample Kolomogorov-Smirnov test (KS; Massey, 1951) is carried out on each pair of samples. The KS statistic on two samples is a non-parametric test for the null hypothesis that the two independent samples are drawn from the same continuous distribution. The decision to reject the null hypothesis is based on comparing the p-value with the significance level set equal to 5%. Moreover, the test allows us to estimate the distance between couples of FDC:

$$\mathrm{D}^{*} = \max_{x}(|F_1(x) - F_2(x)|), \qquad (3)$$

where $F_1(x)$ is the proportion of x_1 values less than or equal to x and $F_2(x)$ is the proportion of x_2 values less than or equal to x. F_1 and F_2 are two FDCs. The KS statistic is applied on daily streamflow data sampled in several periods of record (e.g. 1 year, 10 years, 15 years). The test is carried out both on pairs of samples gauged at the same location in two different years (or in two different decades) and on pairs sampled at two different sites. Since the streamflow data presents autocorrelation, the autocorrelation effects the KS test. Weiss (1978) proposed a methodology to account for modifying the KS test for autocorrelated data. Later, Xu (2014) suggested a method that can be applied to two samples test. The information contained in the data is (usually) less than an i.i.d. sample with the same size. In other words, the number of equivalent independent observations is fewer than the sample size. In the following, we explain how we took into account the equivalent sample size. It is easier to implement and more importantly, it can be easily generalized to two samples test. We can assume that the autocorrelation effect attenuates after three days. For instance, let take as an example a 1 year FDC. If the sample was three times smaller and for instance the length would equal 122 (i.e., 365 divided by 3), the null hypothesis would have been rejected anyway, leading to the same conclusion (i.e., the two samples cannot be regarded as the same distribution). This is due to the fact that, according to the two samples KS test, the length of the equivalent sample that could pass the test should be 22.

The application of the KS test to our samples is pivotal to the development of the methodology. Test results show that streamflow data gauged in different periods (e.g. years or decades) at a specific location do not have the same distribution. The consequence is that it is not possible to use the parameters and the distribution derived from a FDC built for a specific time window to build the FDC of another time window. The same results comparing streamflow data gauged in a specific year or decade at two different sites. Since the two data sets cannot be regarded as the same distribution, it is not possible to derive the FDC at one location using the parameters of a FDC sampled at another location. Therefore, it is necessary to develop a methodology that accounts for the weather as it is main driver of FDCs variability as shown in the following. Figure 4 shows how different can be FDCs built at the same location using streamflow data gauged during different time windows.

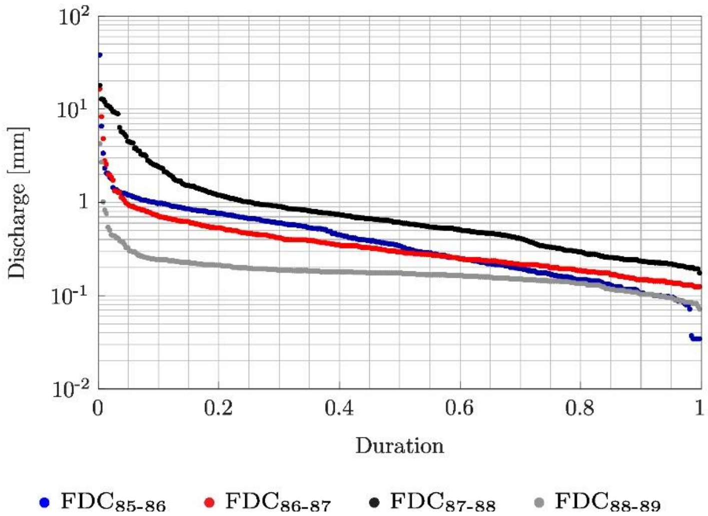

Figure 4. FDCs built for Tangipahoa River (FL) for four different hydrological years. Every hydrological year starts in October and ends the following September.

3 Methodology

The aim of this paper is to find the distribution $Q_k(t)$ for a time period (T_1,T_2), that is a FDC. We assume that discharge is related to precipitation in the form:

$$Q_k(t) = h_k(P_k(t-\tau), \tau = 0, \ldots, n, \ldots, \beta_k), \tag{4}$$

where k stands for the location, h_k is the transformation, usually approximated by a hydrological model, P_k is the precipitation and β_k is the specific parameter of the hydrological model. The core of this work is to retrieve the discharge values without hydrological modelling as modelling is often introducing additional errors and it may be biased for long subperiods. Thus, the main idea is to get rid of a complicated non-linear processes and to find a filter which relates the distributions.

The main hypothesis underlying this work is that daily flow duration curves at a partially ungauged location can be found with knowledge of the precipitation record at a donor site. The most important descriptor of the weather characteristic is the rainfall, however, we cannot use the distribution of P_k to assess the FDC directly as it will fail due to the lacking temporal structure and the many zeros. We can then use a transformation of P_k, the Antecedent Precipitation Index (API):

$$\mathrm{API}(t) = a_k(P_k(t-\tau), \tau = 0, \ldots, n). \tag{5}$$

Both transformations reported in Eq. 4 and 5 can be regarded as filters acting on P_k. These filters do not necessarily produce highly correlated series, but may produce series with similar distributions.

The API is used to investigate precipitation data in a similar way to discharge data as it combines in a streamflow-like way the history of the precipitation. It represents the memory of a basin as it is related to the amount of water released by the soil to the river considering a given time window. Specifically, the API allows us to take into account the antecedent conditions, the duration of the rainfall events and gives an estimate of the portion of rainfall contributing to storm runoff (Linsley et al., 1949). It is a sequence of linear combination of rainfall events in the period preceding a specific storm (Kohler and Linsley, 1951). For a resolution of one day and a time window of 30 days, API at the *i-th* day is given by:

$$\mathrm{API_i} = \sum_{j=0}^{29} \alpha^j P_{i-j}, \tag{6}$$

where α is a constant and ranges from 0 to 1 and P_i is the daily precipitation occurred at the *i-th* day. Since a day-to-day value of the API is required, there is a considerable advantage in assuming α decreasing with the time as shown by Kohler and Linsley (1951). When α tends to zero, API keeps tracks of the precipitation occurred in the few previous days and it represents the short memory of the basin. When α tends to 1, API represents the long memory of the basin as it includes the effect of precipitation occurred many days before. To capture this behavior, in this study α is chosen equal to 0.85, this is in agreement with a previous study by Sugimoto (2014) who investigated one of the two case study areas (i.e. Neckar catchment); nevertheless this value was found to be suitable also for the US catchments. Here the API is calculated from areal precipitation instead of point precipitation.

In the following, the methodology is reported step by step together with the underlying assumptions. Then, the performance criteria used to estimate the goodness of the methodology are presented.

3.2 How to determine the FDC at a partially gauged basin

The assumptions underlying this work are the followings:

I. The cumulative distributions of streamflow and the proxy correlate at a single site over the same period.
II. The exceedance probability of the proxy on a specific day at the donor site is equivalent to the exceedance probability of streamflow on that same day at the target site.
III. The cumulative distribution function of the proxy is identical across sites for both the index site and the target site in the same period.

Where the proxy variable is the variable used to retrieve the FDC at the target site. As the API was used as proxy for the U.S. case area, the first assumption is that the temporal sequence of API exceedance probabilities is highly correlated with the temporal sequence of streamflow exceedance probabilities at a single site over the same period, Table 3.

Table 3. Correlation between temporal sequence of API exceedance probabilities and the temporal sequence of streamflow exceedance probabilities estimated for different sites and different periods.

	Correlation		
Period\Site	Blanco	Tangipahoa	Choctawthachee
1948-1968	0.978	0.996	1
1968-1988	0.995	0.997	1
1948-1963	0.998	0.993	0.998
1948-1958	0.970	0.995	0.998

The second assumption verifies if, for the donor period, the temporal sequence of API exceedance probabilities at the donor site is highly correlated with the temporal sequence of streamflow exceedance probabilities at the target site. This assumption applies for all donor periods; Table 4 shows correlation values for some donor periods.

Table 4. Correlation between temporal sequence of API exceedance probabilities at the donor site (i.e., Blanco River, USA) and the temporal sequence of streamflow exceedance probabilities at three target sites for four different donor periods.

	Correlation			
Sites\Donor period	1948-1968	1968-1988	1948-1963	1948-1958
Tangipahoa	0.996	0.997	0.994	0.997
Choctwhatchee	1	1	0.999	0.999
Bogue	0.990	0.992	0.995	1

The third assumption is that cumulative distribution function of API is identical across sites for both the index site and the target site in the same period. This assumption was verified performing a Kolmogorov-Smirnov test on API at different sites for different periods. For instance, the Weibull distribution is accepted for the API at Tangipahoa, Choctawhatchee and Bogue (USA) for the periods shown in Table 5. However, the distribution parameters may differ from site to site and from time period to time period. The correlation between temporal sequence of API exceedance probabilities at the donor site and at each target site is found to be high, thus the assumption was further verified, Table 5.

Table 5. Correlation between temporal sequence of API exceedance probabilities at the donor site (Blanco, USA) and three other sites is reported for four different periods.

	Correlation			
Sites\Donor period	1948-1968	1968-1988	1948-1963	1948-1958
Tangipahoa	0.98	0.99	0.97	0.99
Choctwhatchee	0.98	0.98	0.98	0.98
Bogue	0.99	0.99	0.98	0.99

In the following, the procedure is explained step by step using the API as a proxy. However, similarly, it is possible to use the streamflow values recorded at the donor site.

Let consider two catchments, A and B. We want to determine the Flow Duration Curve at catchment B from data available at A. Therefore, A is the donor catchment, while B is the target catchment. Let suppose that in a given number of years, discharge is available at both sites A and B, named donor years, while for another number of years, i.e. the target years, data are available for A only.

1. *Donor years selection*. Select a number of years for which precipitation and discharge values are available at daily resolution for catchment A and B, respectively. These will be named donor years (e.g. duration of 1 year, 10, 15, 20 years).
2. *Generation of empirical distribution of API values.* Empirical distributions of API values are calculated for site A for donor and target years: sort API values and assign to each sorted value the corresponding rank and estimate the corresponding frequency of exceedance using the Weibull plotting position.

3. *Generation of empirical distribution of streamflow values.* Empirical distributions of streamflow values are calculated for site B for donor years only.
4. *Data transfer from donor site.*
    i. Select the *i-th* frequency p_i, with $i=1,\ldots,N_t$ where N_t is the length of the target sample, and the corresponding API value recorded at the donor site during the target years, Figure 5a.
    ii. Search for this API value among those recorded at the donor site during the donor years and estimate the corresponding frequency, Figure 5b.
    iii. This frequency is then used to retrieve the corresponding streamflow value recorded at site B during the donor years, Figure 5c.
    iv. This streamflow value is the missing value at site B corresponding to the *i-th* frequency p_i, Figure 5d.

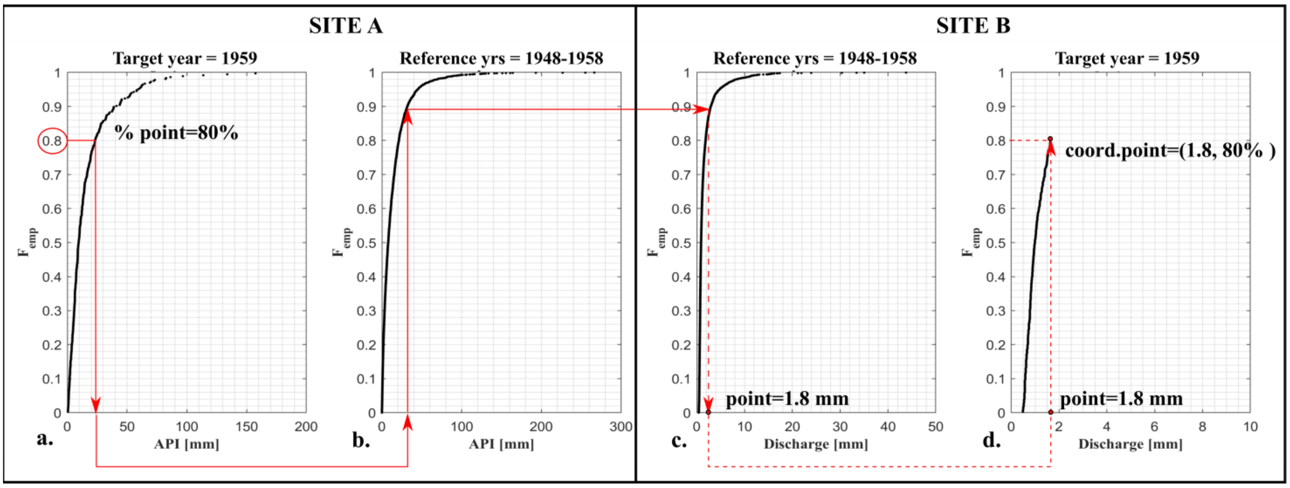

Figure 5. Illustration of FDC generation using the interpolation with the API of the donor site as a proxy.

Steps from 1 to 4 are repeated for every target period and for different target catchments. The FDC is expressed in millimeter, thus the area of the catchment is not an issue using data of another catchment.

An example of the procedure is reported step by step in Appendix A.

3.3 Performance criteria

To determine the performance of the procedure proposed in this paper, different criteria are selected: the Nash-Sutcliff efficiency index (NSE; Nash and Sutcliff, 1970), the BIAS and the mean absolute error (MAE).

The Nash-Sutcliffe efficiency between the interpolated and the observed flow value is the most widespread performance criterion:

$$\mathrm{NSE} = 1 - \frac{\sum_{i=1}^{N}\left(Q_{obs,i}-Q_{intrpl,i}\right)^2}{\sum_{i=1}^{N}\left(Q_{obs,i}-\bar{Q}\right)^2}, \tag{7}$$

where Q_{obs} is the observed discharge value at the target catchment during the target period; $\overline{Q}$ is the mean value of the observed discharge during the target period in the target catchment; Q_{intrpl} is the interpolated discharge value. The NSE is evaluated here for a specific set of percentiles, thus, N is the number of discharge values related to a specific percentile. The **X** percentile is defined as the set containing all "**X**,…" numbers where the dots stand for the decimal points. For instance, the 1.09%, 1.36%, 1.63%, 1.91% belong with the 1rst percentile.

The BIAS represents the mean difference between observed and interpolated values:

$$\mathrm{BIAS} = \frac{1}{N}\sum_{i=1}^{N}\left(\frac{Q_{intrpl,i}-Q_{obs,i}}{Q_{obs,i}}\right). \quad (8)$$

If the BIAS equals zero there is a perfect fit between observed and interpolated values. If the BIAS is negative, observed values are underestimated, while if the BIAS is positive, they are overestimated.

The mean absolute error is defined as:

$$\mathrm{MAE} = \frac{\sum_{i=1}^{N}\left|Q_{obs,i}-Q_{intrpl,i}\right|}{N}. \quad (9)$$

Discharge values are in mm and so the MAE is. It measures the overall agreement between observed and interpolated values. It is a non-negative metric without upper or lower bounds. A perfect model would result in a MAE equals to zero. This estimation metric does not provide any information about under- or over-estimation, but it determines all deviations from the observed values regardless of the sign.

4. Results

The procedure explained above was tested on several target catchments varying both donor and target periods. For the U.S. catchments, using a donor period of 20 years, we considered 10 years and 1 year as target periods. For donor periods equal to 15 and 10 years, we considered as target periods 15 and 10 years, respectively.

Results show a good agreement between observed and interpolated FDCs. For instance, the FDCs interpolated using 20 and 10 years as donor and target periods, respectively, have a good performance, as shown for Tangipahoa and Bogue catchments, Figure 6. The method performance is higher for intermediate durations, while it can be lower for the low flows, e.g. as at Bogue for target years 1988-1998 (Figure 6 lower panels) and for the high flows. The good performance of the approach is also noticeable when the target period is 15 years, Figure 7. On each panel, the two-sample Kolmogorov-Smirnov test distance between observed and interpolated value, D*, is reported. D* is characterized by small values showing a good performance of the method. Since usually the FDC of a donor site is used to retrieve the FDC of a target site for same period, the FDC of the donor catchment recorded during the target period was also plotted. It is noteworthy to observe that the difference between these two FDCs can be substantial. This implies that the FDCs can be substantially different at different sites in the same period of time, in turn it entails that the FDC of a donor site cannot be transferred to another site.

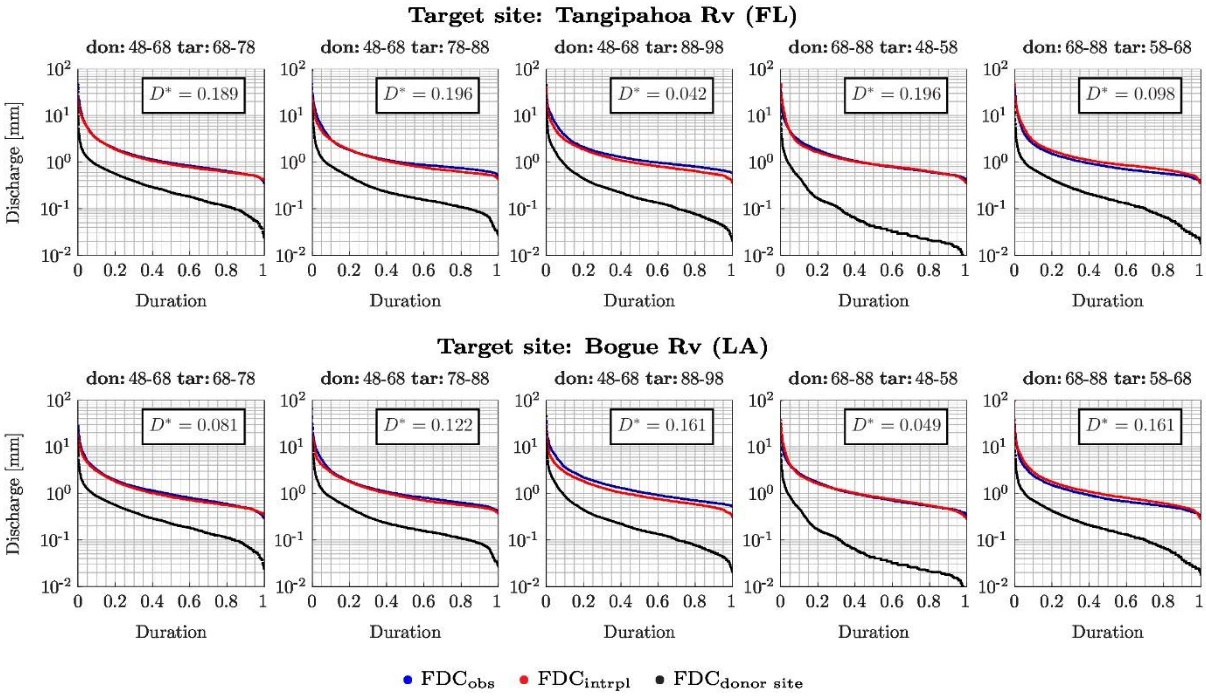

Figure 6. Interpolated FDC at Tangipahoa River (FL) and Bogue River (LA), upper and lower panel, respectively. The donor catchment is Blanco River (TX). The donor years are a 20 years time window from October 1948 to September 1968 and from October 1968 to September 1988. Target years are the decades shown above each panel. Blue dots and red dots are the observed and interpolated FDC at the target catchment, respectively; the black dots are the observed FDC at the donor catchment during the target period.

Interpolated and observed FDCs almost perfectly match when obtained using long donor and target periods, Figures 6 and 7. On the other hand, when the target period is short, the performance decreases as also shown by the KS distance, D*, reported on each single panel of Figure 8 where the target period equals one year. As a matter of fact, the donor period being constant, the KS distance is much higher when the target period is 1 year (Figure 8). Nevertheless, the interpolated and observed FDCs have a high agreement in shape, as for instance at Tangipahoa River for all but one (i.e., 1969-1970) target years. In these cases, the difference between the two curves could be due to the different temperature values characterizing the donor and the target basins. This effects the evapotranspiration in the two basins and therefore, the streamflow values.

Results suggest that the API gives effectively a good estimation of the memory of the basin and can be used to represent the precipitation similarly to the discharge.

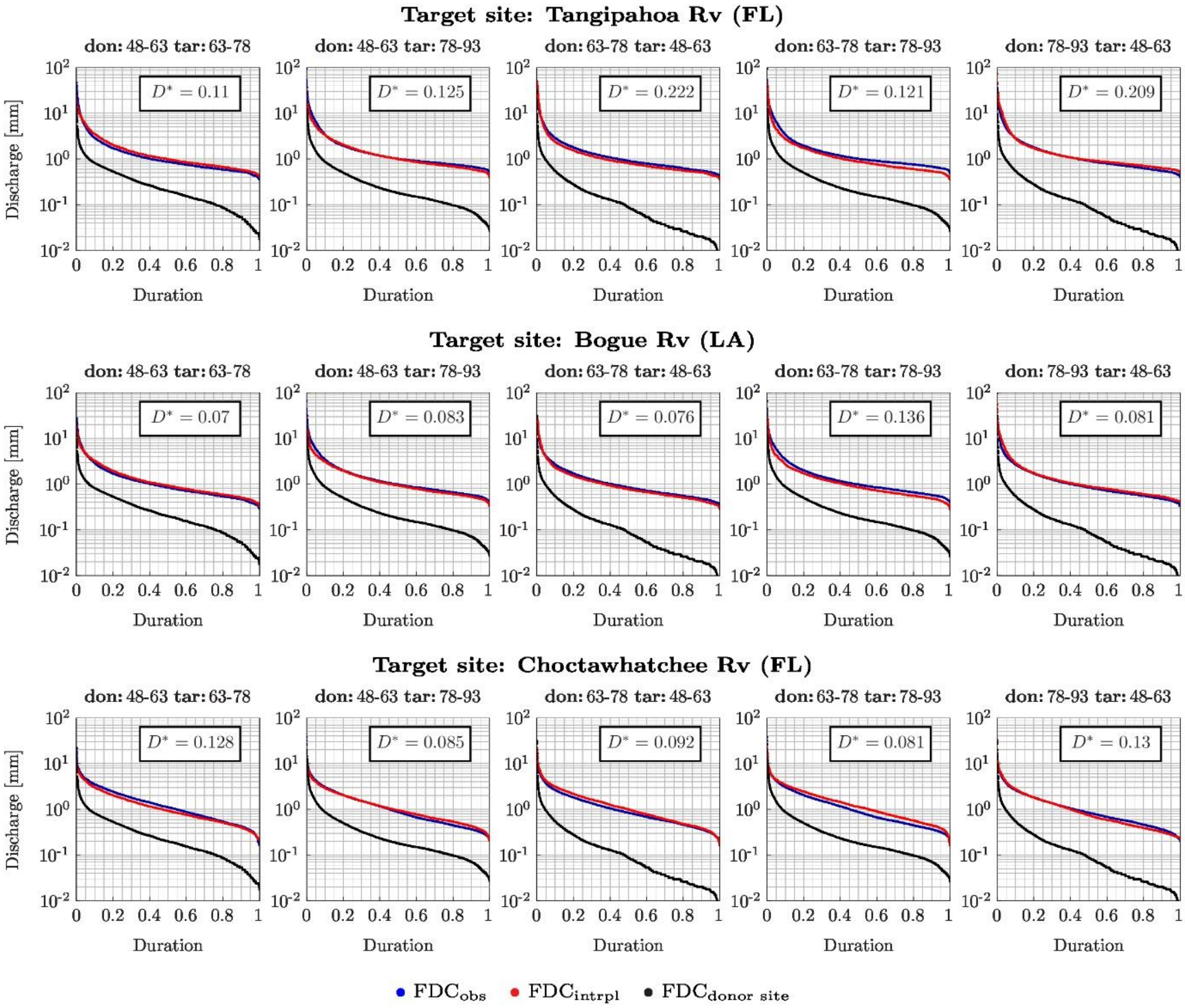

Figure 7. Interpolated FDC at Tangipahoa River (FL), Bogue River (LA) and Choctawhatchee River (FL), upper, middle and lower panels, respectively. The donor catchment is Blanco River (TX). The donor and target years are periods of 15 years. The blue and red dots are observed and interpolated FDC, respectively, at the target catchment, target period; the dots are FDC at the target catchment and the black dots are the observed FDC at the donor catchment during the target period.

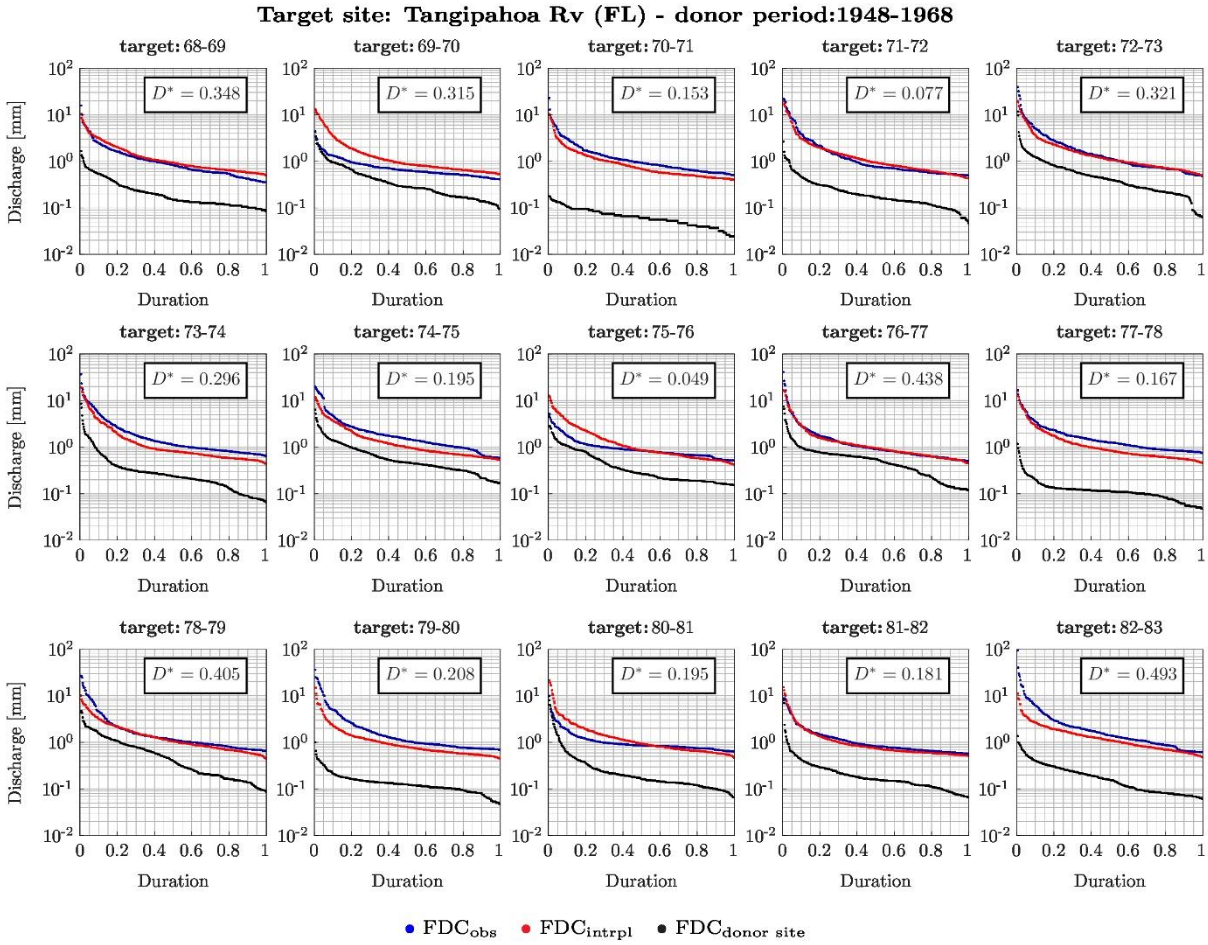

Figure 8. Interpolated FDC at Tangipahoa River (FL).The donor catchment is Blanco River (TX). The donor years are a 20 years time window from October 1948 to September 1968. Target years are each hydrological year from October 1968 to September 1982. The blue and red dots are observed and interpolated FDC, respectively, at the target catchment, target period; the dots are FDC at the target catchment and the black dots are the observed FDC at the donor catchment during the target period.

To estimate the goodness of the methodology, the NSE, BIAS and MAE are evaluated for the 1st, 3rd, 5th, 10th, 20th, 30th, 50th, 75th, 90th and 99th percentiles.

For U.S. catchments, when a decade is used as both target and donor period, the performance measures show a good agreement between observed and interpolated values, Figures 9. The NSE index shows accurate estimation, i.e. it is characterized by values close to 1, especially of intermediate percentiles. The BIAS provides information regarding the over- and underestimation of the observed value. Its magnitude is likely higher for high flows, while it attenuates for intermediate percentiles. Also the MAE shows a low performance for high streamflow values. This is due to the fact that the procedure is more able to reproduce the average streamflow values than extreme events such as high and low flows. However, low flows are more likely well estimated rather than high flows.

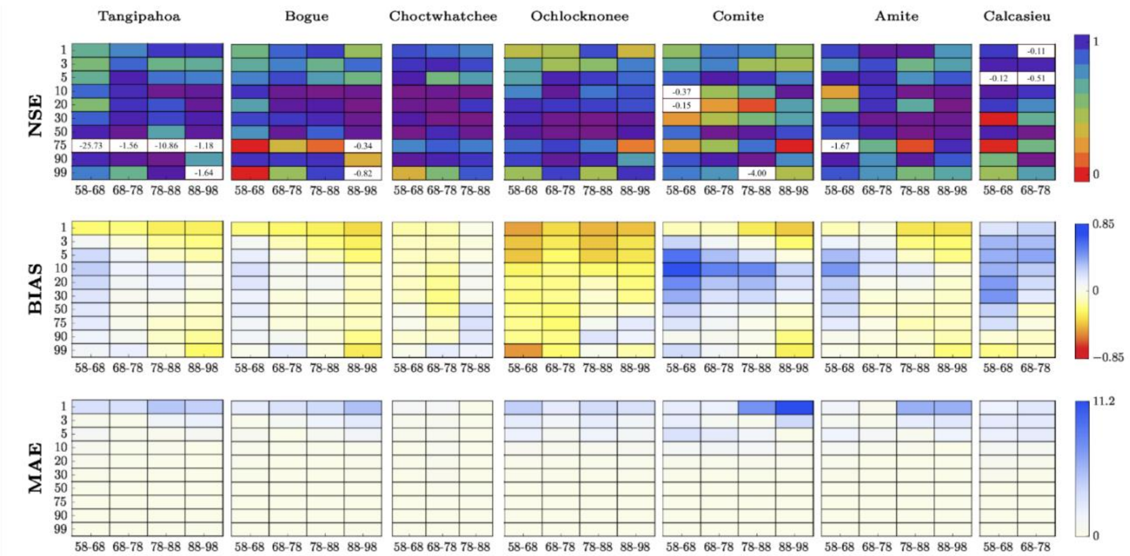

Figure 9. Performance measures NSE, BIAS and MAE evaluated for specific percentiles (on the y-axis) and for specific target decades on the x-axis. The donor decade is 1948-1958, the donor catchment is Blanco (TX). Each target catchment is indicated above the corresponding box. Negative values of the NSE are reported on the corresponding box.

When both target and donor periods equal 15 years, the agreement between interpolated and observed flow values is high, Figure 10. The NSE shows values of efficiency around 1, thus there is a good match between interpolated and observed values, even though there are few exceptions. The errors are very low in value, as shown by the MAE, which also reveals a poor performance for high flows, while the performance improves for intermediate and low flows. The high flows are more likely overestimated, while intermediate and flows are more likely underestimated as shown by the BIAS.

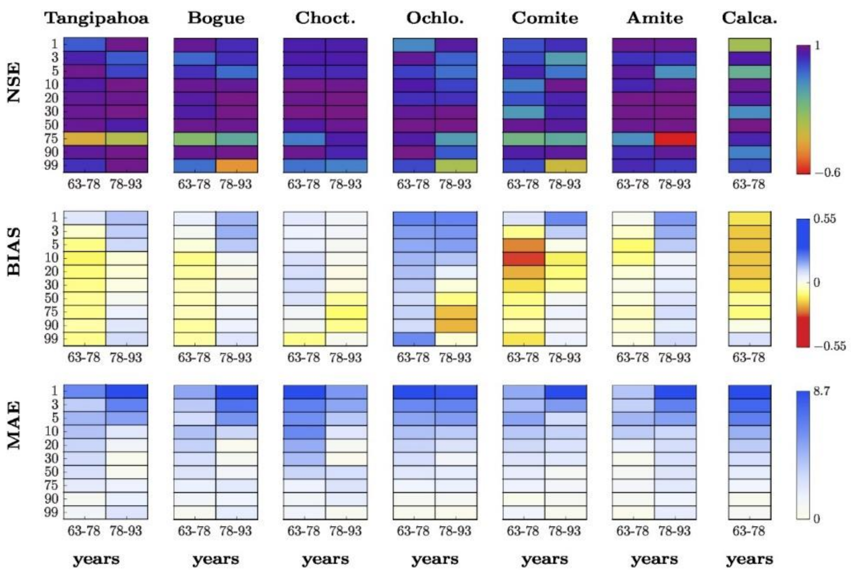

Figure 10. Performance measures NSE, BIAS and MAE evaluated for specific percentiles (on the y-axis) and for a specific 15 target years (i.e., 1963-1978 and 1978-1993 on the x-axis). The donor decade is 1948-1963, the donor catchment is Blanco (TX). Each target catchment is indicated above the corresponding box.

For the German catchments, three different pairs of donor and target years are considered. Test 1 is built using a target time periods of 20 years and a donor period of 10 years. Test 2 is built considering as both donor and target time periods 15 years, while for Test 3, the target time period equals 10 years and the donor one equals 20 years.

We recall that for the German case study the proxy variable is not the API but rather the discharge recorded during the donor period at the donor site. For the German case study, errors are reported for Plochingen Fils, Horb and Oberensingen Aich (henceforth named Aich) as target catchments, using as donor catchment Plochingen Neckar.

As for the U.S. catchments, the estimation metrics show a lower performance for extreme flows. For intermediate percentiles, the NSE shows values closer to 1 and the BIAS is generally close to zero. However, it is worth noticing that the overall agreement between observed and interpolated values is high as demonstrated by a low value of the MAE, Figure 11.

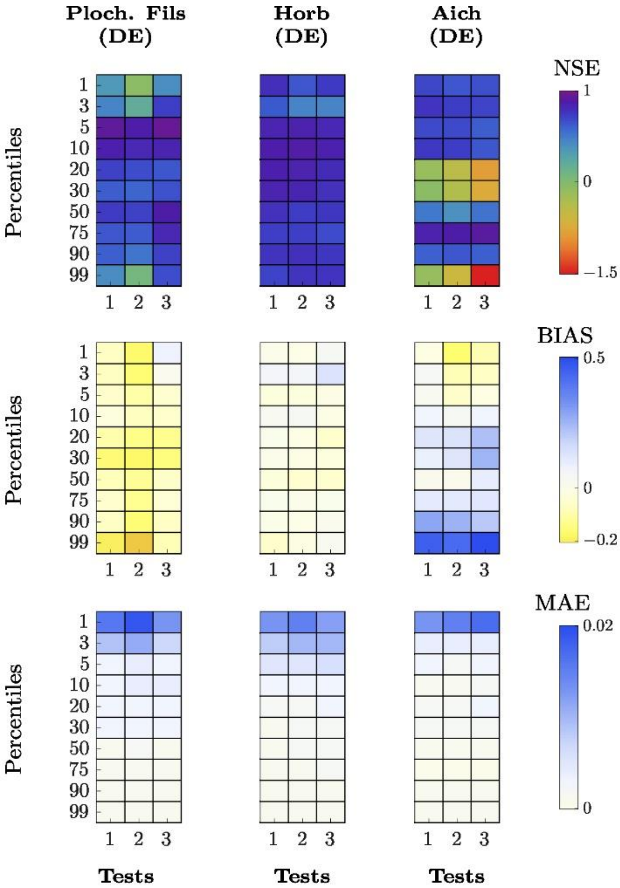

Figure 11. Performance measures NSE, BIAS and Mean Absolute Error (MAE) evaluated for specific percentiles (on the y-axis) and for three specific set of target and donor years (i.e., Test 1, 2 and 3). For Test 1 the target period is from 1961 to 1980 and the donor period is from 1981 to 1990. For Test 2 the target period is from 1961 to 1975 and the donor period is from 1976 to 1990. For Test 3 the target period is from 1961 to 1970 and the donor period is from 1971 to 1990. The donor catchment is Plochingen Neckar, while the target catchments are indicated on each corresponding box.

To better understand the relationship between a target and a donor catchment, the coefficient of correlation has been computed. Coefficient values are reported for all Test cases. Values are estimated between the donor catchment Plochingen Neckar and the three target catchments, Figure 12.

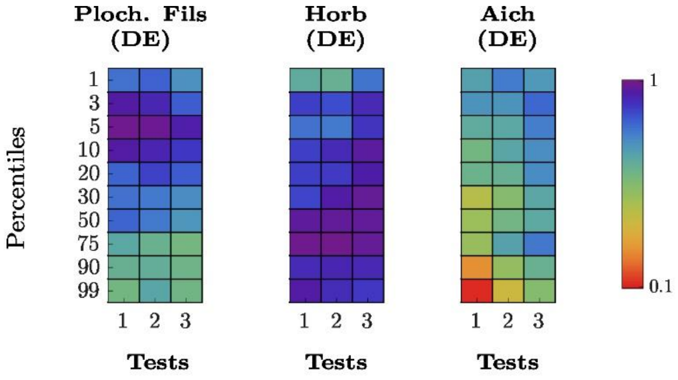

Figure 12. Correlation coefficient evaluated for each Test case at each percentile between Plochingen Neckar and each other catchment indicated on the boxes.

It is interesting to observe that the correlation coefficient shows the same trend of the NSE, as it shows a higher correlation where the NSE is closer to one, while generally they both decrease in correspondence of the same percentiles. The correlation coefficient shows how the proxy variable, in this case the discharge gauged at the donor site, co-moves with the target variable. As expected, where the correlation is high, there is a better estimation of the flow values. Therefore, this means that it is possible to know *a priori* whether a site is more suitable to be a donor site or not. If the correlation is low, also the performance of the method is expected to be low.

5. Discussion

As resulted from the KS test applied to pairs of FDCs obtained from recorded data at the same site in different periods, FDCs cannot be considered an invariant characteristic of a basin. The fact that FDCs are not invariant suggests that the weather is a driver of annual runoff variability. Indeed, the reason should be found in the weather conditions as others (e.g. the catchment area, the land use) did not change. To better investigate these findings, we performed the KS test on pairs of observed and interpolated FDCs for two purposes. The first is to know if pairs of interpolated and observed FDCs at the same site have the same continuous distribution, the second is to know which is the distance between these pairs. The test performed on pairs of interpolated and observed FDCs revealed that the null hypothesis could not be rejected for nearly the half of the cases. For instance, for Tangipahoa River the test was not rejected in 48% of the cases, Figure 13. On the contrary, the test rejected the null hypothesis that FDCs built at the same location in different periods had the same distribution. In the 73% of the cases, the distance between pairs of interpolated and observed FDCs of the same period is smaller than the distance between FDCs built at the same site from data recorded during different periods, Figure 13. These results suggest that the methodology proposed here has a good performance and it is actually an interesting alternative to other methodologies, which assume that FDC of different periods of time have the same distribution.

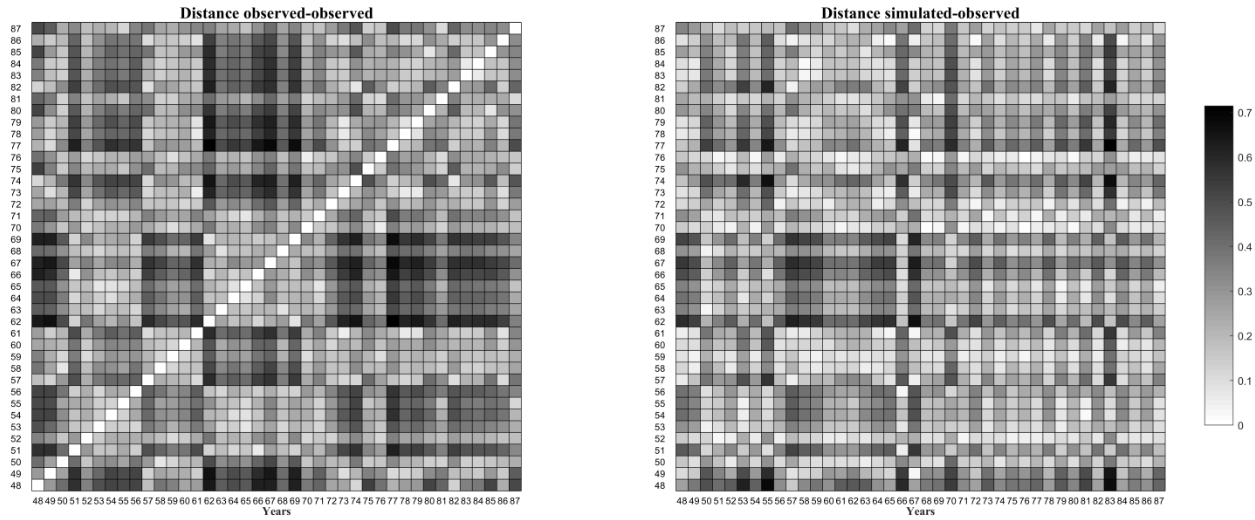

Figure 13. Kolmogorov-Smirnov distance between couples of streamflow values observed (left panel) and between couples of streamflow values observed and interpolated (right panel) at Tangipahoa River (FL) from October 1948 to September 1987.

As the weather conditions strongly influence the FDCs estimation, we analyzed the streamflow percentiles to assess the between-year variability. To this end, the moving average (MA) of 30th, 70th, 90th and 95th percentiles of streamflow is estimated. The MA values are estimated using three different fixed time windows (i.e., 10, 15 and 20 years), Figure 14.

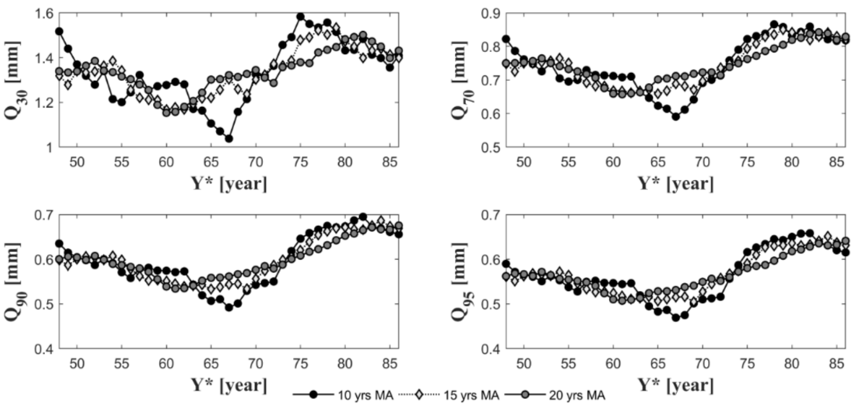

Figure 14. Moving average (MA) of the 30th, 70th, 90th and 95th percentiles of daily streamflow values gauged at Tangipahoa. Three different fixed time windows are used to estimate the MA: 10, 15 and 20 years. On the x-axis the first year of each interval is plotted (Y*).

It is interesting to observe that the MA values are characterized by a strong variability throughout the time. The fluctuation of the flow percentiles suggests that the percentiles cannot be considered an invariant characteristic of the basin. Therefore, it is not possible to estimate the flow quantiles using regression methods that do not take into account the weather characteristics. These methods, first, regionalize empirical runoff percentiles using multiple regression models. Then, regional evaluation of flow percentiles are interpolated across the percentiles (e.g., Franchini and Suppo, 1996; Smakhtin, 2001). If flow percentiles are estimated separately from weather characteristics, it may results in a misrepresentation of the percentiles themselves. Therefore, we suggest to add a weather factor to take into account the influence of the weather in the percentiles estimates.

6 Conclusions

The paper presents a new, simple and model free methodology to estimate the streamflow behavior at partially gauged catchments, given the discharge and the precipitation gauged at another catchment. We show that two FDCs built for the same catchment with data corresponding to two different time windows, cannot be regarded as the same continuous distribution. This means that the FDCs cannot be considered an invariant characteristic of a basin. As other conditions did not substantially change across time, such as the land use, the reason should be the weather. The influence of the weather is evident analyzing the between-year variability of flow percentiles. Indeed, the moving average of the 30th, 70th, 90th and 95th flow percentiles shows a strong variability throughout the time. This behavior has a strong consequence as it means that it is not possible to retrieve the streamflow percentiles without taking into account the weather. Indeed, there exists several methodologies (i.e., regression models) that estimate flow quantiles separately from weather characteristics. FDCs and their selected properties cannot be considered as catchment characteristics and should be used with caution for regionalization purposes. The FDC at a specific site is not a property of the corresponding basin, but the FDC is a property of both the basin and the weather. Therefore, it is not possible to infer a FDC using parameters retrieved from the distribution of another FDC without considering the weather.

Because of the dependence on the climate, discharge data are here retrieved using the precipitation data series. Since precipitation data series are characterized by a high number of zeros, here we used the Antecedent Precipitation Index (API). The API is used as it represents in a streamflow-like way the precipitation of the basin. It represents the memory of a basin providing the amount of precipitation released by the soil throughout the time.

The FDC at a target site is determined for a specific time window (i.e., target period) using API and discharge available for a so-called donor period at another catchment (i.e., donor site).

To test the methodology, several donor and target periods are analyzed, such as 1 year, 10, 15 and 20 years and two case study areas are investigated, one located in USA and the other one in Germany. Interpolated FDCs are compared with FDCs that were actually observed. From the comparison of observed and interpolated FDCs, it results that the methodology is able to correctly determine the missing streamflow data. The discharge values of the intermediate percentiles are better described than those of the extremes. Nevertheless, the error values between observed and interpolated FDCs are small. The difference between the interpolated and observed FDCs can be due to the different temperature values characterizing the donor and target catchments. Indeed, a high difference in temperature can cause a different evapotranspiration, which in turn can influence the discharge. To better analyze the relationship between donor and target catchments, the coefficient of correlation is computed between discharge data gauged at the two sites of interest during the donor period. As the performance criteria highlighted, the data series are more related at the intermediate percentiles and less at the extremes. The correlation coefficient estimated for the donor period can help to determine in advance whether the discharge data of a donor and a target catchments are strongly correlated during that period of time. The FDCs interpolated at the target site will be more accurate if the correlation coefficient shows a strong correlation.

Appendix A

In this Appendix we want to provide an easy example to better understand the method that we applied for U.S. catchments. This method is based on the use of the API of a donor site to retrieve the FDC at a poorly gauged site. We recall that a “donor period” is a period of time for which streamflow values are available at both donor and target catchments, while a “target period” is a period of time during which streamflow values are not available at the target catchment. As the rainfall is available at both sites for both periods, also API values are.

Let suppose that we want to know the discharge value at catchment B (i.e., Bogue Rv, LA) corresponding to the 10.11th percentile (i.e., 10.11%) for the year ranging from October 1968 to September 1969. Let suppose that the donor period has a length of 15 years. Every hydrological year ranges from October to September of the following year. We present the method step by step in the following.

1. Select the mean daily precipitation occurred at the donor catchment (i.e., Blanco Rv) during the target period and estimate the API as in Eq.6 assuming α equal to 0.85;

2. sort in descending order the API values evaluated for the target period at the donor catchment (i.e., Blanco Rv, TX);

3. assign to each sorted value the corresponding rank i, with i = 1,..., N_t where N_t is the length of the target API series and thus equals 365, and then estimate the exceedance probability $P(Q < q_i)$ of each value using a Weibull plotting position $i/(N_t + 1)$, Table A1;

4. in the sorted API series, identify the value with frequency equal to 10.11%. This value equals 37.72 mm (bold line in Table A1);

5. estimate the API from the mean daily precipitation occurred during the donor period at the donor catchment (i.e., Blanco Rv, TX) and sort in descending order the API values, estimate the rank and the associated exceedance probability $P(Q < q_j)$ of each value as $j=(N_r + 1)$ where N_r equals 5475;

6. find the exceedance probability $P(Q < q_j)$ associated to the value 37.72 mm in the sorted API sample. From Table A2 it is possible to observe that there is not such an API value. Therefore, look for the two most similar values: one should be bigger and the other smaller than the searched value. Then, take their empirical frequency values (i.e., 7.52 % and 7.54%; in bold, Table A2);

7. sort in descending order the streamflow values gauged during the donor period at the target catchment (i.e., Bogue Rv, LA), estimate the rank and the associated exceedance probability $P(Q < q_j)$ of each value as $j=(N_r + 1)$;

8. find the two streamflow values which have an empirical frequency equal to 7.52 % and 7.54%. These values are in bold, Table A3;

9. estimate the mean value of these two streamflow values. The resulting value is the streamflow value with empirical frequency equal to 10.11% evaluated for the target catchment and the target period that we were looking for, Table A4.

Table A1. API values sorted in descending order and the corresponding percentiles estimated for the target year (i.e., 1968-1969) at the donor catchment (i.e., Blanco RV, TX).

Rank	$P(API<API_i)$ %	$API_{Blanco, tar}$ mm
1	0.27	76.78
2	0.55	73.39
…	…	…
30	8.20	39.65
31	8.47	39.35
32	8.74	38.71
33	9.02	38.31
34	9.29	38.18
35	9.56	38.10
36	9.84	37.97
37	**10.11**	**37.72**
38	10.38	36.99
…	…	…
365	99.73	0.61

Table A2. API values corresponding to specific percentiles estimated for the donor years (i.e., 1948-1963) at the donor catchment (i.e., Blanco RV, TX).

Rank	$P(API<API_j)$ %	$API_{Blanco, ref}$ mm
1	0.02	266.17
…	…	…
410	7.49	37.81
411	7.51	37.78
412	**7.52**	**37.74**
413	**7.54**	**37.61**
414	7.56	37.61
415	7.58	37.55
…	…	…
5475	99.98	0.01

Table A3. Streamflow values corresponding to specific percentiles gauged during the donor years (i.e., 1948-1963) at the target catchment (i.e., Bogue RV, LA).

Rank	$P(Q<q_j)$ %	$q_{Bogue,ref}$ mm
1	0.02	38.81
…	…	…
410	7.49	3.28
411	7.51	3.28
412	**7.52**	**3.21**
413	**7.54**	**3.21**
414	7.56	3.20
415	7.58	3.19
…	…	…
5475	99.98	0.31

Table A4. Streamflow value corresponding to the 10.11th percentile estimated for the target year (i.e., 1968-1969) at the target catchment (i.e., Bogue RV, LA).

$P(Q<q_i)$ %	$q_{Bogue,tar}$ mm
10.11	3.21

Competing interests. No competing interests are present.

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