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Downscaling stream flow time series from monthly to daily scales using an auto-regressive stochastic algorithm: StreamFARM

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SUMMARY

Downscaling methods are used to derive stream flow at a high temporal resolution from a data series that has a coarser time resolution. These algorithms are useful for many applications, such as water management and statistical analysis, because in many cases stream flow time series are available with coarse temporal steps (monthly), especially when considering historical data; however, in many cases, data that have a finer temporal resolution are needed (daily).

In this study, we considered a simple but efficient stochastic auto-regressive model that is able to downscale the available stream flow data from monthly to daily time resolution and applied it to a large dataset that covered the entire North and Central American continent. Basins with different drainage areas and different hydro-climatic characteristics were considered, and the results show the general good ability of the analysed model to downscale monthly stream flows to daily stream flows, especially regarding the reproduction of the annual maxima. If the performance in terms of the reproduction of hydrographs and duration curves is considered, better results are obtained for those cases in which the hydrologic regime is such that the annual maxima stream flow show low or medium variability, which means that they have a low or medium coefficient of variation; however, when the variability increases, the performance of the model decreases.

1. Introduction

A large number of applications require the availability of stream flow data at a detailed temporal resolution, such as water supply reliability, reservoir operations, management of water resources, and analysis of low frequency flow. In many cases, historical series are composed of data at coarse temporal resolution (e.g., monthly; see Smakhtin, 2000) and only a subset of the available stations have data at higher temporal resolution (e.g., daily). In other cases, for the same measurement station, older data are at coarse resolution while recent data are at higher resolution because sensors have changed and improved over the years or automatic data transfer systems have been installed. Looking at various global and countrywide datasets (see Section 2.1), it can be seen that in many cases only monthly data are available.

For these reasons, the need to downscale stream flow data arises, especially for some applications, such as statistical studies of extreme values or for water management purposes.

In the case of very large basins (with an area O(Area) $> 5 \times 10^5$ km^2), the yearly maximum daily flow and the yearly maximum monthly flow are comparable because the response time of the catchment is on the order of several weeks or more (Maidment, 1992). If we consider small and medium size basins (O(Area) $< 10^4$ km^2), the yearly maximum daily flow is smaller than the instantaneous peak flows during a day (that is, hourly or lower values) and is not representative of the criticality of the flow event, and, in some cases, the yearly maximum daily flow occurs on a different day with respect to the maximum values at lower time scales. Daily time series can be used for water resource management; however, they are not an optimal solution for extreme event analyses. Finally, there is a wide range of basin categories for which carrying out extreme statistical analysis on daily data is reliable because yearly maximum daily flow is good quantitative indicator of the instantaneous peak flow, and the maximum daily and monthly flows are not significantly different.

This results in the need to set up methodologies to downscale large amounts of monthly data to daily time resolution.

Many methodologies have been presented over the past years to disaggregate annual to seasonal flow, seasonal to sub-seasonal

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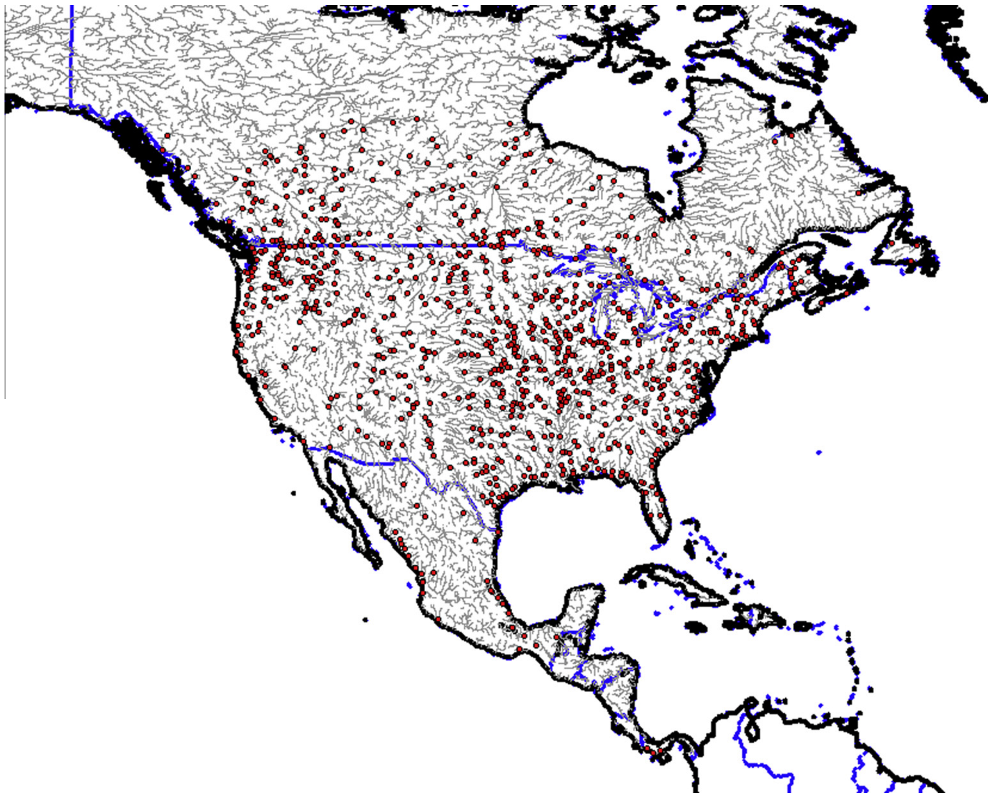

Fig. 1. Map of Central and North America with the locations of the level gauge stations.

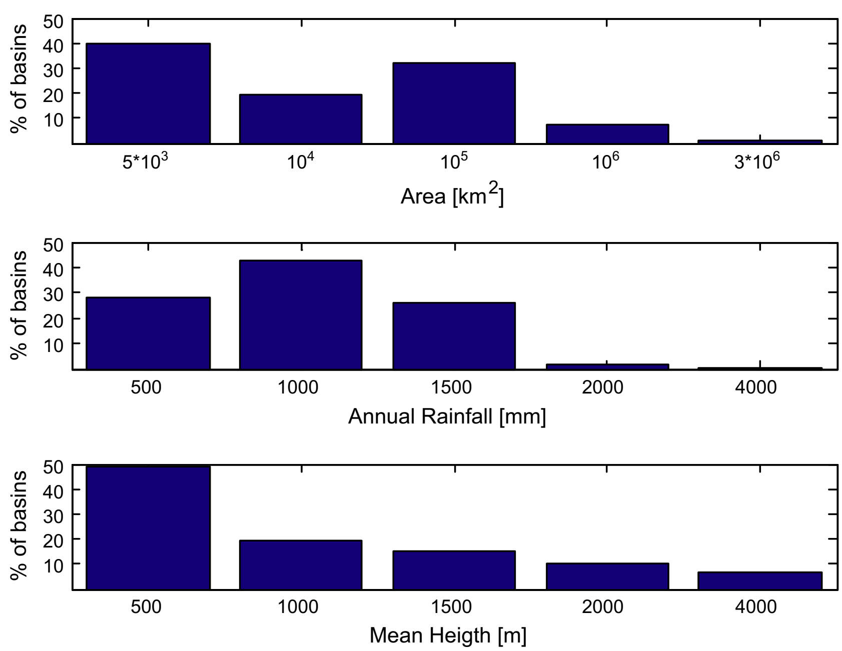

Fig. 2. The hydro-climatic characteristics of the considered basins. The histograms show the distribution of drainage area (Area), the mean annual rainfall (Annual Rainfall), and the mean height of the basin (Mean Height).

flow, and monthly to daily flow. Lane (1979) and Salas et al. (1980) proposed techniques to divide annual flows into seasonal flows, Koutsoyiannis and Manetas (1996) developed a method to disaggregate annual flow into monthly or weekly amounts, Lall and Sharma (1996) presented a K-nearest-neighbour (K-NN) bootstrap approach to time series modelling and applied it to stream flow simulation, and Tarboton et al. (1998) developed a kernel-based approach for annual to monthly stream flow disaggregation.

More recently, Smakhtin (1999, 2000) implemented a technique to establish daily flow duration curves from monthly data that allows establishing relationships between monthly and daily predefined quantiles. Koutsoyiannis (2001) described a stepwise

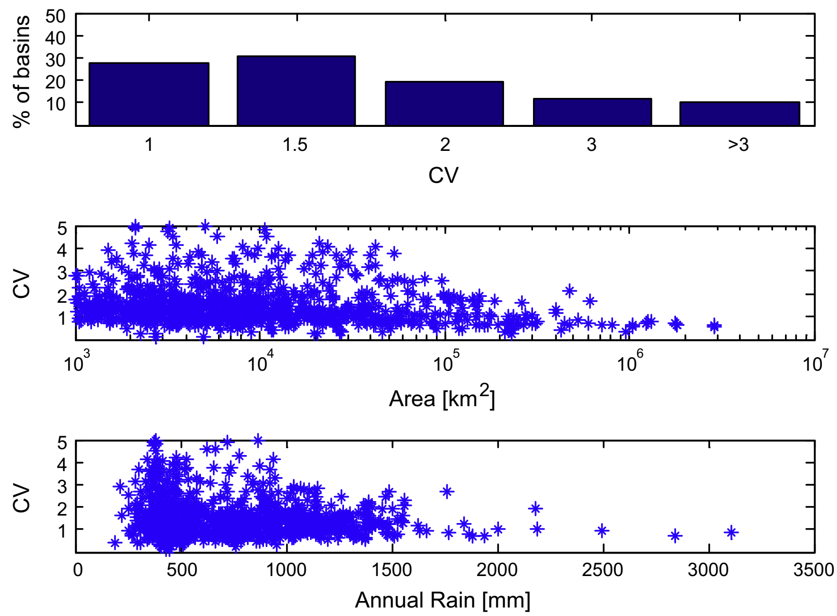

Fig. 3. The top panel shows the percentage of basins that belong to the various classes of CV of the AMDS (*x*-axis). The middle and bottom panels show the relationship between the CV of the AMDS and the drainage area (Area, *x*-axis in log scale) and the mean annual rainfall (Annual Rainfall), respectively.

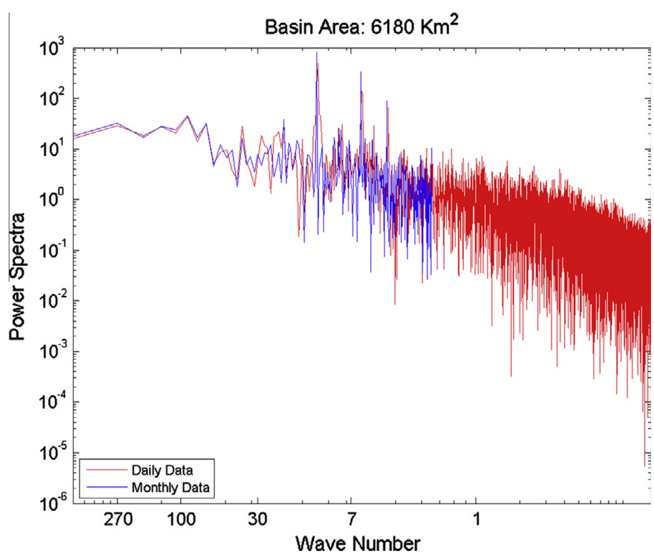

Fig. 4. Power spectrum for a daily time series (red) and the corresponding monthly time series (blue). (For interpretation of the references to colour in this figure legend, the reader is referred to the web version of this article.)

disaggregation scheme that preserves certain higher-order statistics maintaining their temporal and spatial dependencies. Kumar et al. (2000) adopted a technique based on the K-nearest neighbour with an optimization scheme for spatial and temporal disaggregation of monthly stream flows to daily flows. In general, nonparametric nearest neighbour methods have been applied to a variety of hydro-climate modelling issues, including stochastic daily weather generation (Rajagopalan and Lall, 1999; Yates et al., 2003). Prairie et al. (2007) presented a method to resample monthly flow conditioned on the annual values in a temporal disaggregation or at multiple-upstream locations. Acharya and Ryu (2014) disaggregated monthly data at a target station based on the monthly counterparts at a source station.

Many of these techniques are quite complex and need an optimization process to be applied; in some cases, they also need iterative processes that could be computationally demanding (Koutsoyiannis, 2001; Prairie et al., 2007). Several techniques require a specific hypothesis regarding the relations of the flow series between different nested stations and expect that complete daily series are available on one or more stations in the analysed catchment (Kumar et al., 2000); in this case, the disaggregation is considered to be the solution of an optimization process for each time step of the available data (e.g., monthly).

This work analyses a method that follows an autoregressive approach (Rebora et al., 2006a,b). It uses a filtered autoregressive model to generate possible daily stream flow time series using the monthly data as input. The algorithm has a stochastic term that allows it to produce a number of possible daily flow time series. All of these time-series maintain the volumes at the monthly time scale of the input data but have a different behaviour

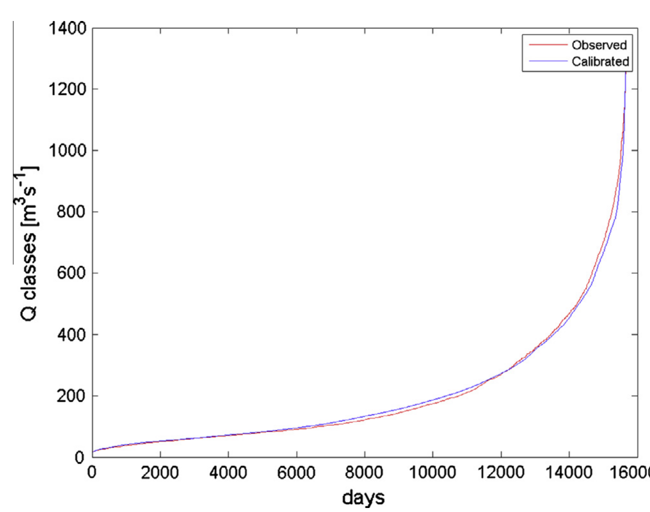

Fig. 5. Example of calibration on a station with Area = 147,807 km^2 comparing the observed and calibrated duration curves.

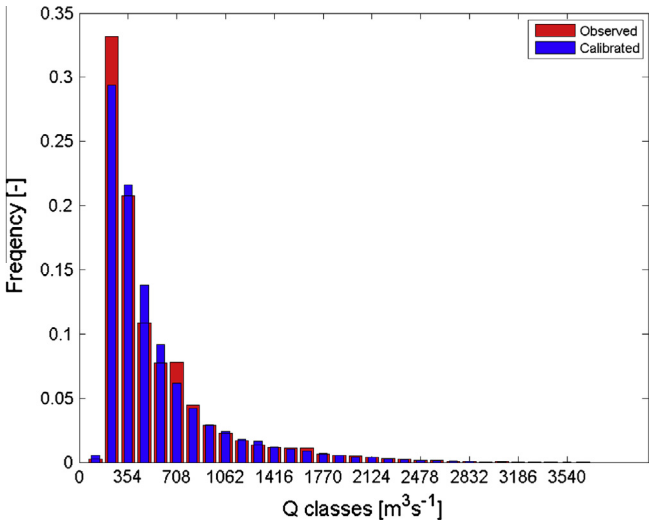

Fig. 6. Example of calibration on a station with Area = 147,807 km^2 comparing the observed and calibrated probability density functions (PDFs) in terms of the frequency histogram.

at the daily scale. It is easy to implement and not computational demanding and can be especially useful when high temporal resolution (e.g., daily) time series need to be generated without the constraint of spatial disaggregation (e.g., statistical analysis).

The method was implemented, calibrated, and verified on a very large stream flow dataset with data from 919 stream gauge stations that covered the entire North and Central American Continent.

The paper is organized as follows: Section 2 describes the dataset, Section 3 presents the algorithm and the calibration–validation method, Section 4 shows the results in the study area, and, in Section 5, comments and conclusion are reported.

2. Dataset

2.1. River discharge dataset

The discharge stations dataset is based on different data sources providing time-series of monthly and daily discharge values. These sources provide various compilations of national or regional stations' datasets.

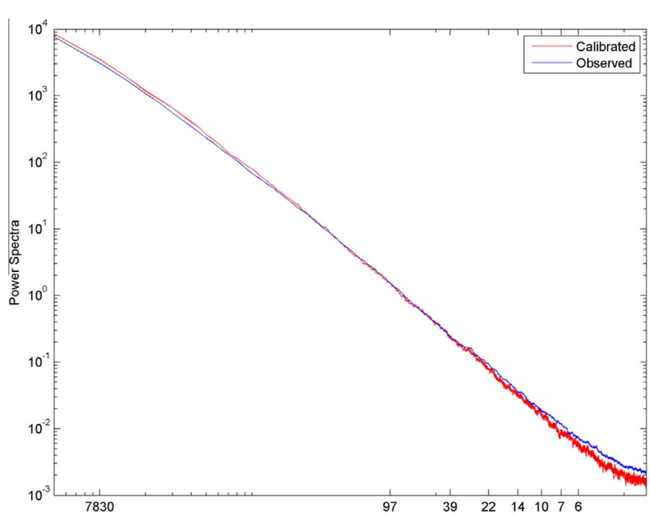

Fig. 7. Example of calibration on a station with Area = 147,807 km^2 comparing the power spectra derived by the observed and modelled daily stream flow series.

In the following, the data sources reported are:

- The long-term mean monthly and daily discharge dataset of the Global Runoff Data Centre (GRDC), 56002 Koblenz, Germany (available at http://www.bafg.de/GRDC/EN/Home/homepage_node.html); and
- The Global River Discharge Database (RivDIS v1.1) of the Water Systems Analysis Group, Complex Systems Research Center at the Institute for the Study of Earth, Oceans and Space, University of New Hampshire (available at http://www.rivdis.sr.unh.edu/ or alternatively at http://www.sage.wisc.edu/riverdata/).

We considered North and Central America as a study area because a large number of stations with long daily time series are available (especially in Canada and the United States). The sub-set of 919 stations was chosen because they have daily stream flow time-series with durations greater than 40 years (Fig. 1).

The majority of the stations are located in the United Sates, with a rather homogeneous distribution over the territory; only the southwest shows a lack of data, likely due in part to the presence of deserts.

The southern part of Canada is again well covered, even if the gauge density is lower than in the United Sates, while in Mexico and other countries in Central America, only a small number of stations are available and they are not very well distributed over the territory.

2.2. Meteoclimatic and digital elevation model dataset

The precipitation derived from the Climatic Research Unit (CRU) time-series datasets of the variations in climate, with the variations in other phenomena, has been used to estimate the meteoclimatic characteristics of the considered catchments in terms of mean annual precipitation.

The morphologic characteristics (Area and Mean Height) were derived using the following sources of data:

- The Digital Elevation Model (DEM) NASA Shuttle Radar Topography Mission (SRTM) SRTM version 2 provided by the National Geospatial-Intelligence Agency (NGA) and the National Aeronautics and Space Administration (NASA); and
- The NASA Shuttle Radar Topography Mission (SRTM) Water Body Data provided by the National Geospatial-Intelligence Agency (NGA) and the National Aeronautics and Space Administration (NASA).

2.3. Hydro-climatic characterization of the considered basins

The data presented in the previous sections were used to characterize the basins upstream of the stations of the dataset and to synthetically describe their hydrologic regime. Fig. 2 shows the hydro-climatic characteristics in terms of drainage area, height, and rainfall regime. Of the basins, 60% have a drainage area smaller than 10^4 km^2 and approximately 30% have a drainage area between 10^4 km^2 and 10^5 km^2; 28% have an arid climate with annual precipitation less than 500 mm, 4–5% have a tropical climate with annual precipitation greater than 2000 mm, and the other basins have a semi-arid, temperate, or cold climate. Approximately 50% of the basins have a mean elevation lower than 500 m while approximately 15–16% are in alpine conditions with mean elevation greater than 2000 m.

Fig. 3 shows graphs based on the coefficient of variation (CV) of the annual maxima daily stream flow (AMDS), which is used as an index to describe the flow regimes of the considered stations.

The top panel of Fig. 3 indicates that approximately 28% of the stations have a low variability of AMDS with CV < 1, approximately 30% have a CV between 1 and 1.5, approximately 30% of the

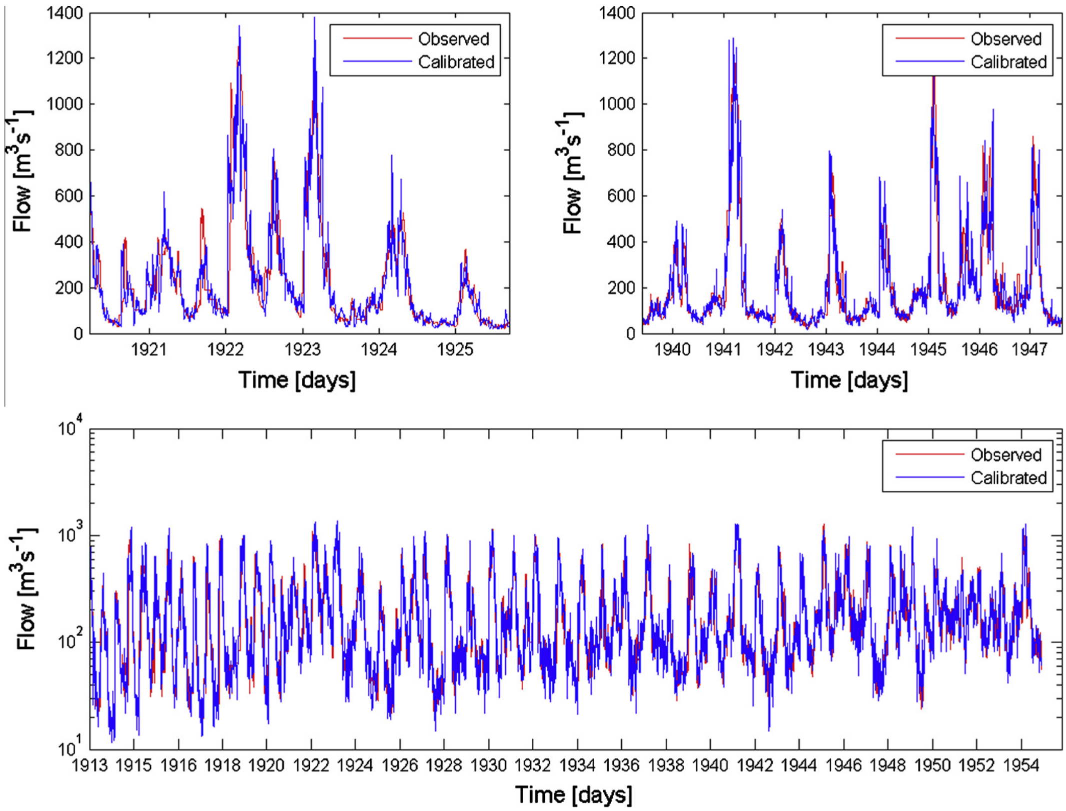

Fig. 8. Example of calibration on a station with Area = 147,807 km^2. In the bottom subplot the entire observed and modelled (calibrated) daily time series are shown. The upper figures display the details of two specific periods.

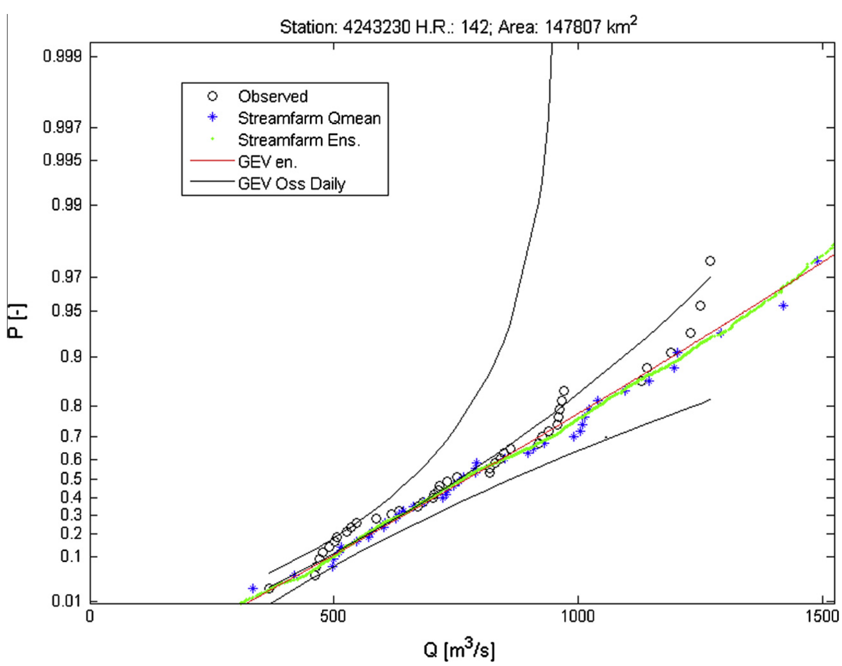

Fig. 9. Distribution of the maximum daily stream flow of a station with Area = 147,807 km^2. The black dots are the observations, and the black lines are the fitted GEV distributions and its 95% confidence interval. The green points are the $D * M$ annual daily maxima, and the red line is the fitted GEV distribution. The blue points represent the series of D daily maxima obtained by the average of M realizations. (For interpretation of the references to colour in this figure legend, the reader is referred to the web version of this article.)

stations have a CV between 1.5 and 3 displaying a quite high variability of AMDS, and 10% of the stations have a very high variability of AMDS (CV > 3).

As shown in the other two panels of Fig. 3, this variability can be related to the size of the upstream catchment; however, it is primarily due to the rainfall regime of the catchment. Arid and

Table 1
Results of the StreamFARM validation on Test basin 1 with Area = 33,910 km^2. The Mean and the Standard Deviation of the statistics were obtained from the N (N = 100) stream flow time series generated with StreamFARM.

Statistic	Mean	Standard deviation
NS on hydrograph	0.729	0.0131
NS on duration curve	0.997	0.0017
RE on hydrograph	0.3018	0.0038
RE on duration curve	0.0422	0.0015

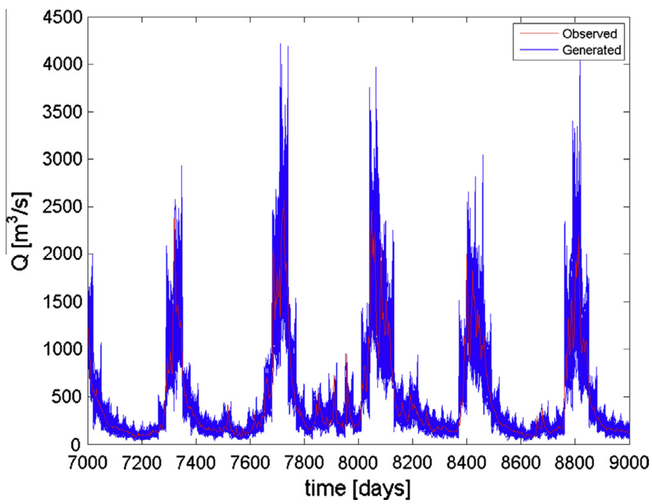

Fig. 10. Test basin 1 with Area = 33,910 km^2. Ensemble of the possible daily stream flow histories generated with StreamFARM compared to the observations.

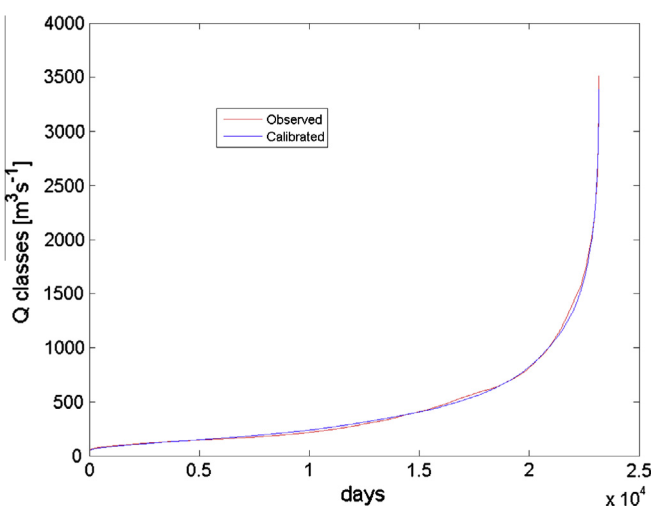

Fig. 11. Test basin 1 with Area = 33,910 km^2. The observed and calibrated duration curves. Time is on the x-axis and the daily stream flow is on the y-axis.

semi-arid catchments with total mean annual rainfall <1000 mm can experience very different AMDS from one year to another resulting in high values of CV.

3. Methods

3.1. Downscaling stream flow from monthly to daily series with StreamFARM

The StreamFARM model is based on an autoregressive approach presented by Rebora et al. (2006b) and applied by Rebora et al. (2006a) and von Hardenberg et al. (2007) for rainfall downscaling. It is based on a filtered auto-regressive model capable of generating an ensemble of possible daily stream flow time series that are equal to the monthly data used as input if aggregated at a monthly scale.

Table 2
Results of the StreamFARM validation on Test basin 2 with Area = 14,290 km^2. The Mean and the Standard Deviation of the statistics were obtained from the N (N = 100) values obtained for each statistic.

Statistic	Mean	Standard deviation
NS on hydrograph	−0.512	0.0906
NS on duration curve	0.957	0.0022
RE on hydrograph	2.13	0.0805
RE on duration curve	0.857	0.0102

The model starts from the monthly data on a specific river section. As an example we define a time series of % months with a monthly (averaged) time step. These data are labelled $Q(T)$. In this description, all of the capital letters indicate data at monthly time steps (large scale), while all of the small letters indicate data at daily time steps (small scale).

In the following, we report the steps needed to generate, in ensemble mode, high-resolution daily discharge starting from monthly averages.

(1) First, we estimate the slope of the power-spectrum of the $Q(T)$ time series. To do this we obtain the Fourier transform of $Q(T)$ whose power spectrum in Fourier space (reported as a blue line in Fig. 4) is indicated as:

$$|\hat{Q}(\Omega)|^2, \tag{1}$$

where Ω is the wave number (monthly data).

(2) Then, we generate a power spectrum indicated by the red line in Fig. 4 whose spectral slope is defined according to the power law:

$$\omega^{-\beta}, \tag{2}$$

where ω is the wave number (daily data) and β represents the first free parameter of the model, which can range from 3 to 1.

We use small letters and change the name of the variable because now the signal has increased its time resolution (from monthly to daily, even if in Fourier space) according to the power law:

$$|g(\omega)|^2 \sim \omega^{-\beta} \tag{3}$$

(red line in Fig. 4).

(3) Next, we generate the Fourier spectrum by adding uniformly and randomly distributed Fourier phases. The result is as follows:

$$\hat{g}(\omega) = |g(\omega)|\, e^{i\phi(\omega)}, \tag{4}$$

where $\phi(\omega)$ is uniformly and randomly distributed and changes from one ensemble member to the next. By inverting the Fourier spectrum we obtain a Gaussian field in physical space, $g(t)$, with a daily time resolution but with a Gaussian distribution of its values.

(4) We generate a daily discharge time series via exponentiation of the Gaussian field according to the exponential law:

$$\tilde{q}(t) = e^{\alpha[g(t)]}, \tag{5}$$

where α represents the second free parameter in the model.

(5) Finally, we force the discharge values, $\tilde{q}(t)$, of the generated daily discharge time series to be equal to the series $Q(T)$ when aggregated at a monthly scale. This guarantees that each daily time series is equal to the monthly time series if averaged at this scale. This results in the following operation:

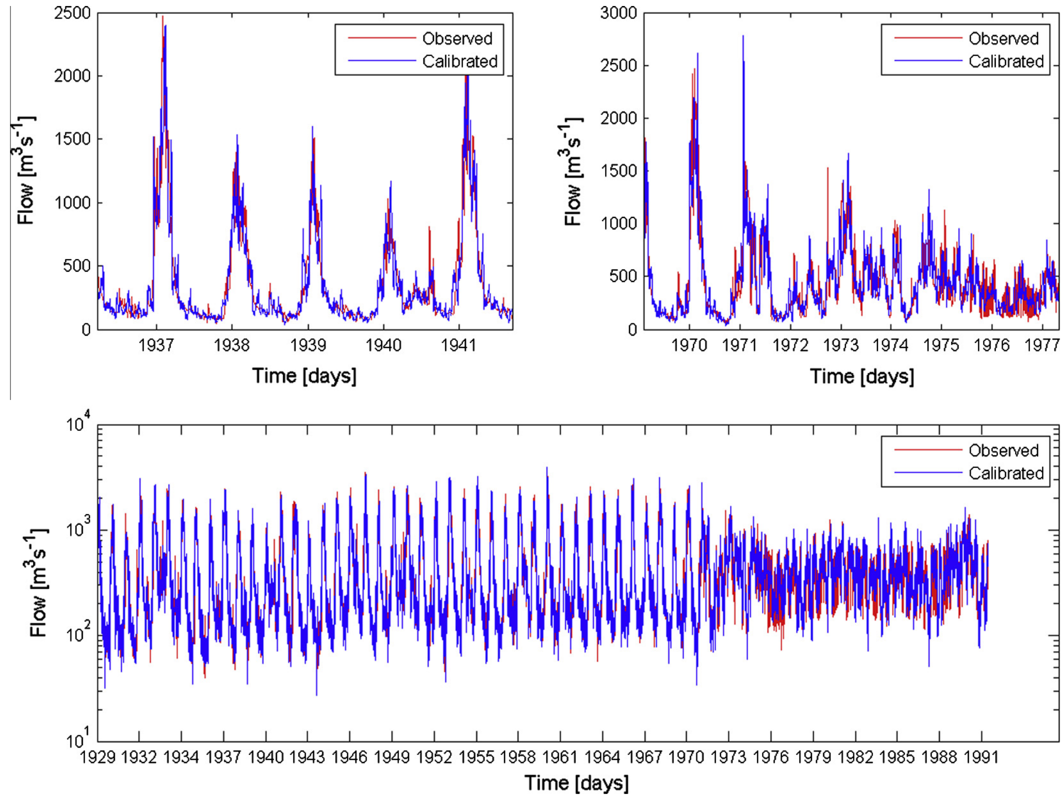

Fig. 12. Test basin 1 with Area = 33,910 km^2. The observed and simulated daily stream flow time series. In the bottom panel, the entire observed and modelled daily time series are reported. This series demonstrates the introduction of a dam that changes the river regime. The top panels represent details of two specific periods.

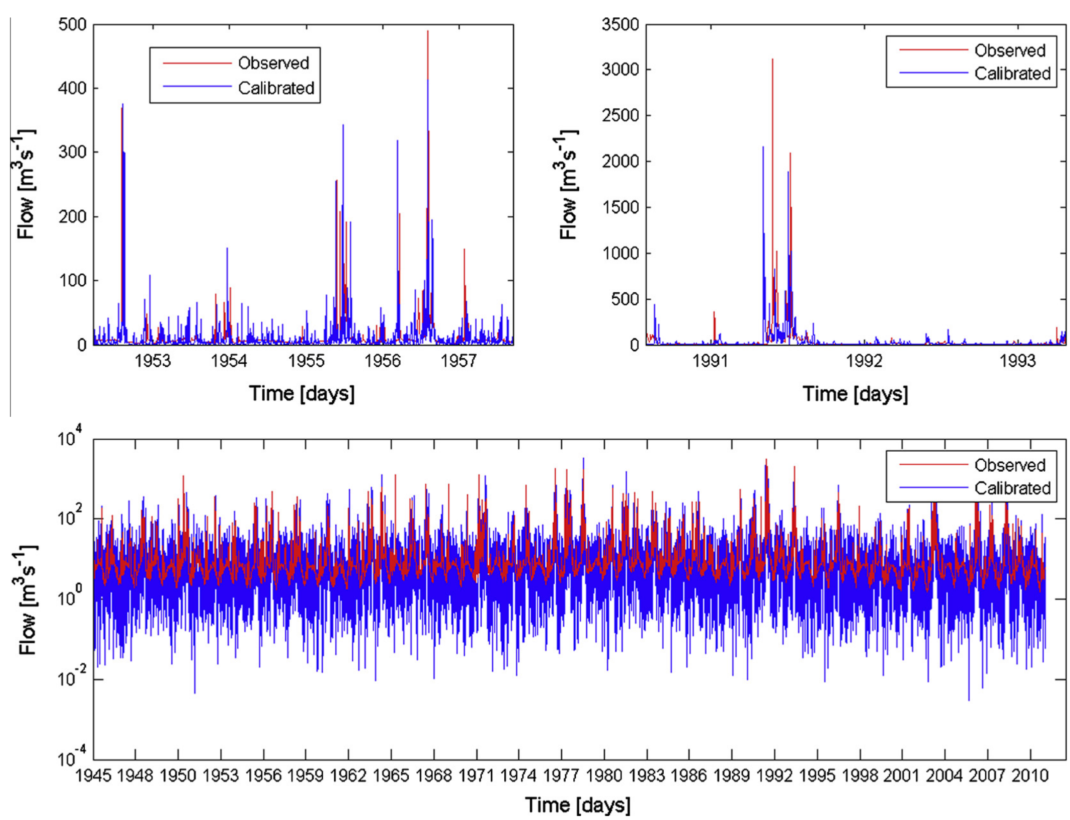

Fig. 13. Test basin 2 with Area = 14,290 km^2. The observed and calibrated daily stream flow time series. In the bottom panel, the entire observed and modelled daily time series are reported. The upper panels represent details of two specific periods.

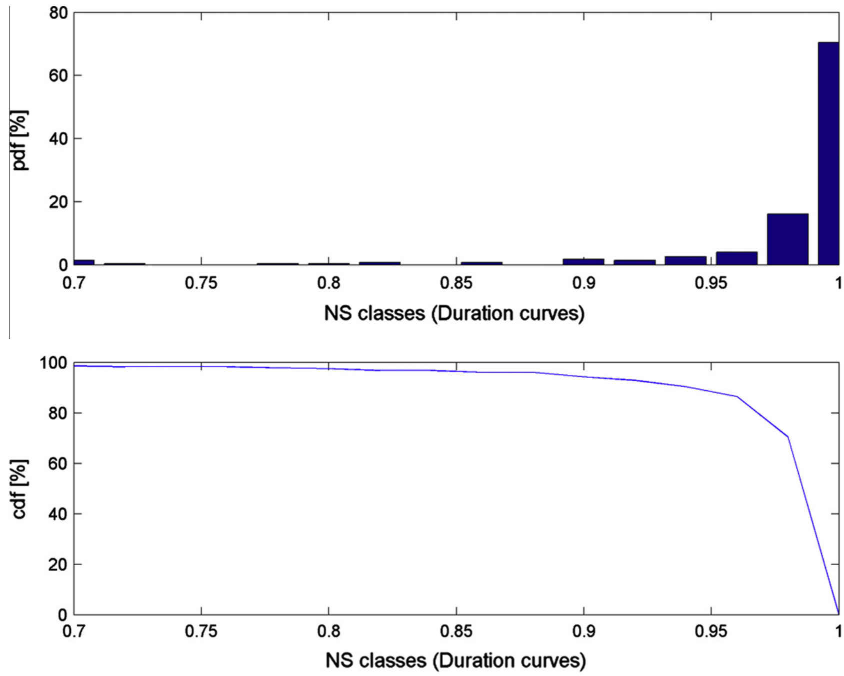

Fig. 14. NS of the duration curves for the 919 stations in North and Central America that were considered. The upper panel shows the PDF of the NS estimated on the duration curves. The bottom panel reports the CDF (Cumulative Density Function) of the NS estimated on the duration curves.

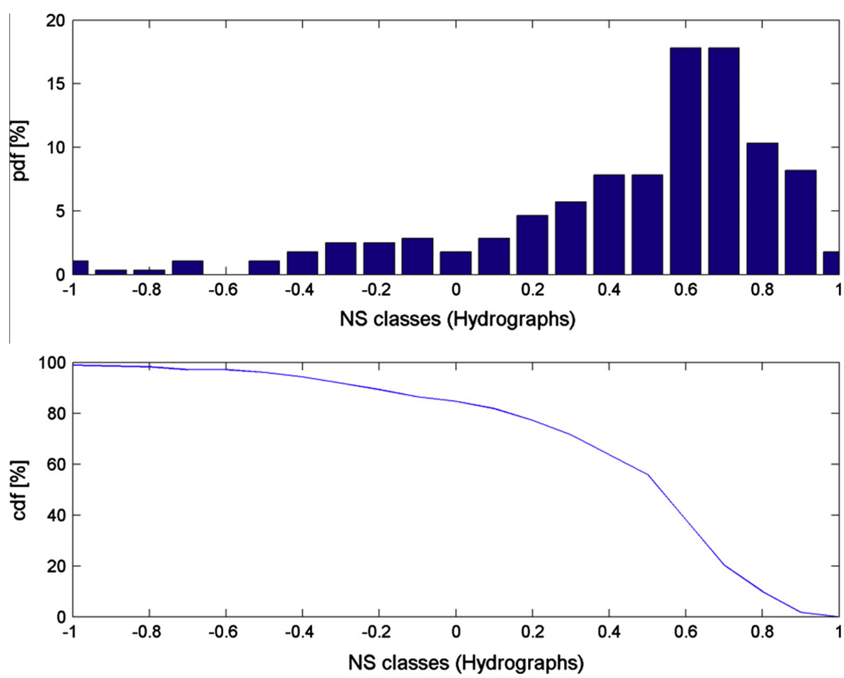

Fig. 15. NS of the hydrographs for the 919 stations in North and Central America that were considered. Upper panel: the PDF of NS estimated on the hydrographs. Lower panel: the CDF of NS estimated on the hydrographs.

$$q(t) = \tilde{q}(t)\frac{Q(T)}{\tilde{Q}(T)}, \tag{6}$$

where $\tilde{Q}(T)$ represents the time series of $\tilde{q}(T)$ averaged at the monthly scale.

The proposed model takes into account the differences in the average monthly stream flow due to changes in the discharge regime (e.g., the introduction of a dam).

In the following sections, we show how the values of the two free parameters α and β can be estimated.

3.2. Parameter estimation

The parameter estimation is carried out in a sub-period of the entire period where daily data are available for two reasons: (i) to conduct a sample validation or (ii) a common occurrence where

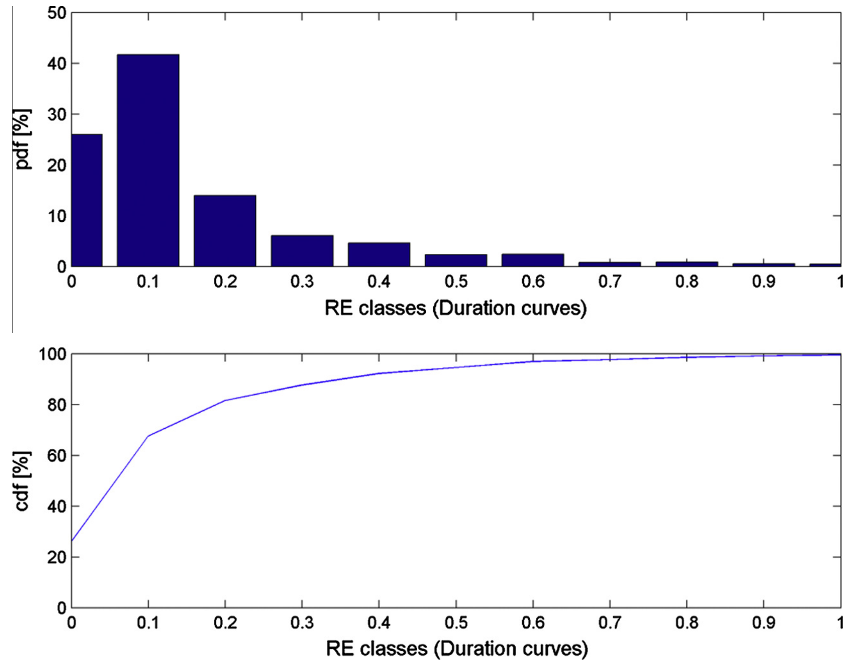

Fig. 16. RE of the duration curves for the 919 stations in North and Central America that were considered. Upper panel: PDF of RE estimated on the duration curves. Lower panel: CDF of RE estimated on the duration curves.

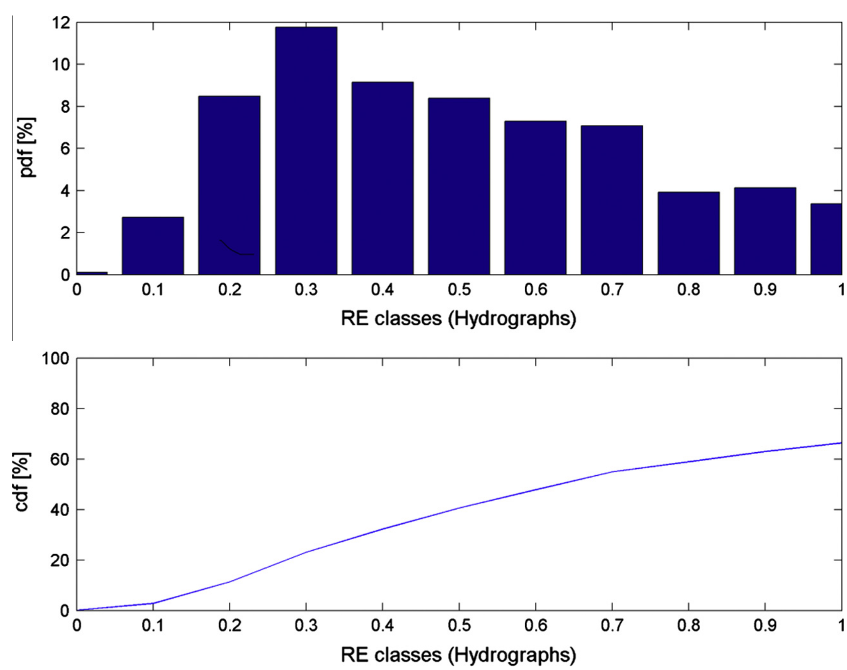

Fig. 17. RE of the hydrographs for the 919 stations in North and Central America that were considered. Upper panel: PDF of RE estimated on the hydrographs. Lower panel: CDF of RE estimated on the hydrographs.

daily data are available for a reduced period of time and there is the need to generate likely daily time series for those periods where only monthly data are available. The estimation is performed for each section referring to the duration curves obtained by ordering the daily stream flow data; the objective is to reproduce the daily data from a statistical point of view, giving less importance to the temporal history of the daily stream flow. In this study, a unique parameter set is calibrated for each section and used for all of the calibration–validation periods.

The calibration steps are the following:

(1) Daily time series are sorted to obtain the observed duration curves.
(2) Daily time series are aggregated at the monthly scale to reproduce a case where only monthly data are available.
(3) For a fixed number of values of the two StreamFARM parameters (α and β), a possible daily time series is generated starting from the monthly data.

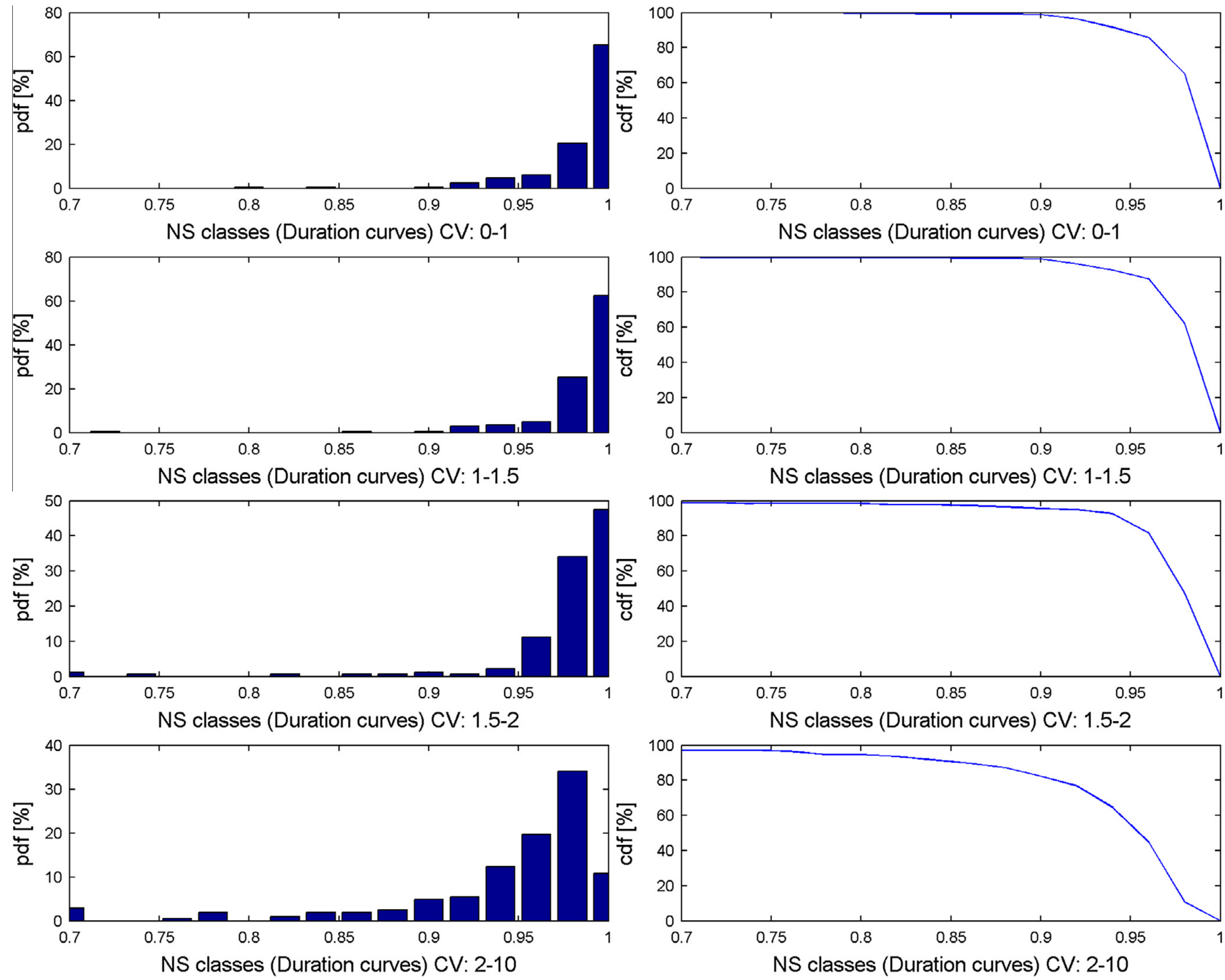

Fig. 18. NS of the duration curves. Results are shown for different classes of CV. Left column panels: PDFs of NS. Right column panels: CDFs of AE.

(4) The two StreamFARM parameters (α and β) are tuned to minimize the differences between the observed and modelled duration curves obtained by sorting the time series. The two considered ranges are $\alpha \in [0.5\text{–}2]$ and $\beta \in [1\text{–}3]$, therefore 500 combinations of parameters are generated and the best parameter set is found by minimizing the following objective function:

$$Err = \frac{1}{T_{max}} \sum_{j=1}^{T_{max}} \frac{|Q_{o,j} - Q_{s,j}|}{Q_{o,j}}, \tag{7}$$

where T_{max} is the number of days of the calibration period, j is the jth day, Q is the daily stream flow, and o and s stand for observed and simulated variables, respectively.

(5) Because the StreamFARM model is probabilistic, the calibration processes (in particular for steps 3 and 4) are repeated N times (e.g., $N = 100$) generating N couples of parameters that are all best sets (they are generally very similar) $\alpha_{best,i}$ and $\beta_{best,i}$ with $I = 1,2,\dots,N$.

(6) The final calibrated parameters are estimated by averaging the two parameters series of length N.

In Fig. 5, an example of calibrated and observed duration curves is shown.

Fig. 6 shows a comparison of the observed and simulated stream flow Probability Density Function (PDF).

Fig. 7 shows a comparison between the observed and simulated power spectra of the stream flow.

In Fig. 8, a comparison between the observed daily data and a history of the daily stream flow generated with StreamFARM is shown. In this case, the matching between the two hydrographs is quite good. This is not always possible, and the pattern at the daily scale can be quite different depending on the dimensions of the basin and its hydrological regime.

Because an interesting statistical property of a stream flow time series is the AMDS, its distribution has been generated and compared to the observations (Fig. 9). The black dots are the observations, and the black lines are the fitted GEV (Hosking and Wallis, 1993; Kottegoda and Rosso, 1997) distribution and its 95% confidence intervals. StreamFARM was initially used in ensemble mode, therefore, as results, we have a number M of possible time series of length D (years) and $D * M$ annual maxima that we fitted with a GEV distribution (Fig. 9, red line and green points). For each year, the average of the M annual maxima was calculated, and the obtained time series of length D is plotted in Fig. 9 (blue points) to show how representative it is of the sample. Fig. 9 demonstrates that the three series are within the confidence intervals of the observations and that the two modelled series of AMDS (of length

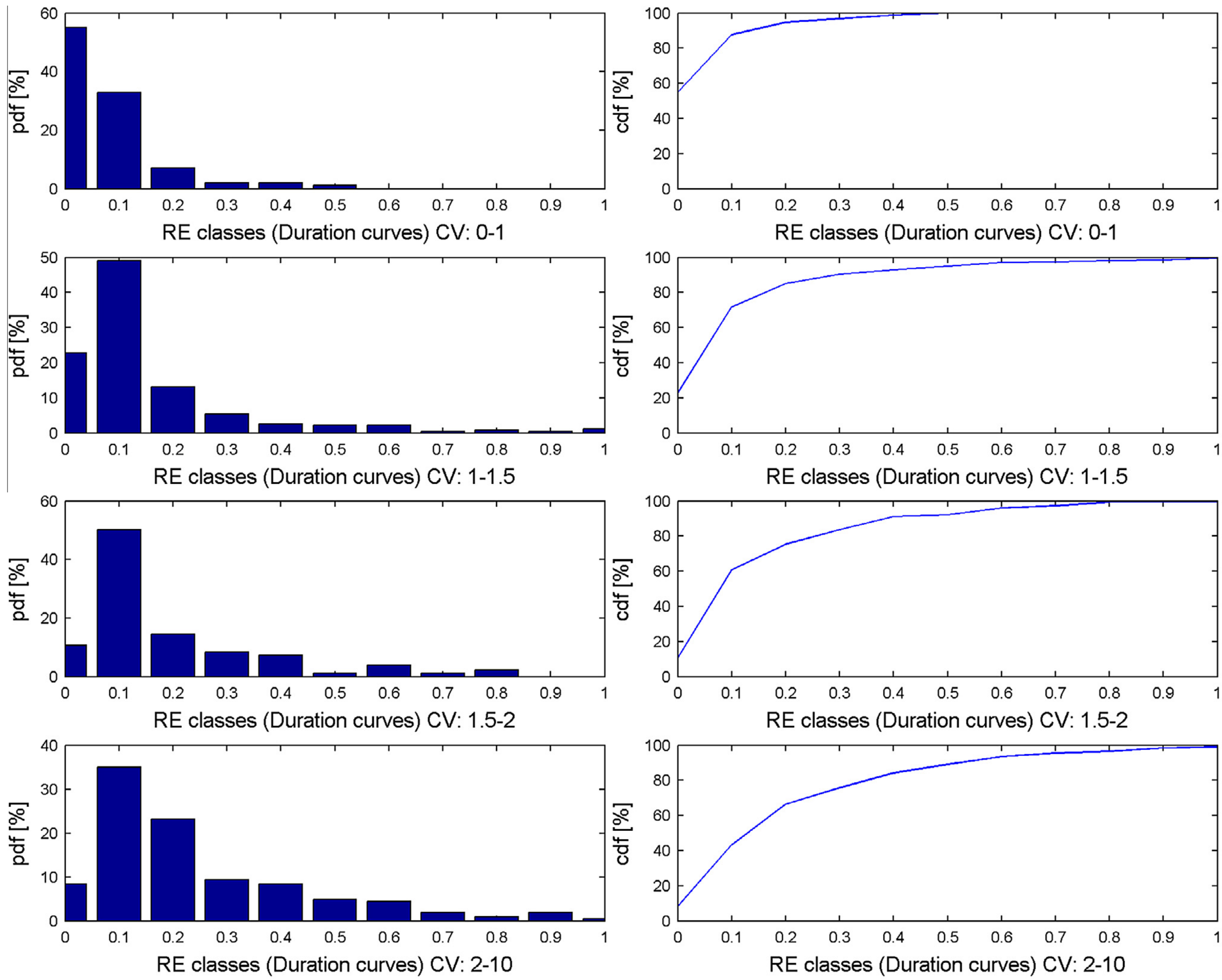

Fig. 19. RE of the duration curves. Results are shown for different classes of CV. Left column panels: PDFs of RE. Right column panels: CDFs of RE.

$D * M$ and of length D) are able to represent the same statistical distribution.

4. Results

4.1. Application, calibration, and validation of two test cases

The application of the methodology was first conducted on a test case (Test basin 1) to view the complete process of calibration and verification of StreamFARM. Then, a second test case was considered to illustrate the possible spread of results that could be obtained (Test basin 2); verification was achieved by calibrating the model on a subset of daily data and by reproducing the entire available period. Test basin 1 features the introduction of a dam upstream of the station, which is evident from the permanent decrease in the variance of the stream flow series after a well-defined year. From a total sample of 68 years of data, the first 20 years were used for calibration while the entire series is used for validation. In the validation phase, $N = 100$ possible daily stream flow histories were generated. The comparison was conducted in terms of the Nash Sutcliffe (NS; Nash and Sutcliffe, 1970) coefficient and the relative error (RE). The RE is defined as:

$$\mathrm{RE} = \frac{1}{n}\sum_{i=1}^{n}\frac{|Q_{si} - Q_{oi}|}{Q_{oi}}, \tag{8}$$

where n is the length of the time series, Q is the stream flow, and s and o stand for simulated and observed variables, respectively.

The observed and simulated stream flows were compared using both hydrographs and duration curves. In Table 1, the average and standard deviations of NS and RE are shown.

The values of the statistics indicate good performances, especially when the duration curves are considered. In fact, the NS value for the duration curve is approximately 1 (meaning a perfect matching between model and observations) and its RA is approximately 0 (RA = 0 indicates a perfect match between model and observations); moreover, the values of the statistics are stable because the standard deviation is low with respect to the mean. In the case of hydrographs, RE and NS perform less well because the sub-monthly time series are likely reasonable and reproduce the observations well (in statistical terms); however, they are far from the real temporal sequence.

Fig. 10 shows the ensemble of daily stream flow histories generated with StreamFARM. In the test case, the observed stream flow always lays within the ensemble; however, this is not always respected and depends on how much the daily sequence is influenced by factors that cannot be captured by the monthly time series.

For the sake of simplicity, graphs are hereafter shown considering only one possible daily stream flow time series generated by StreamFARM.

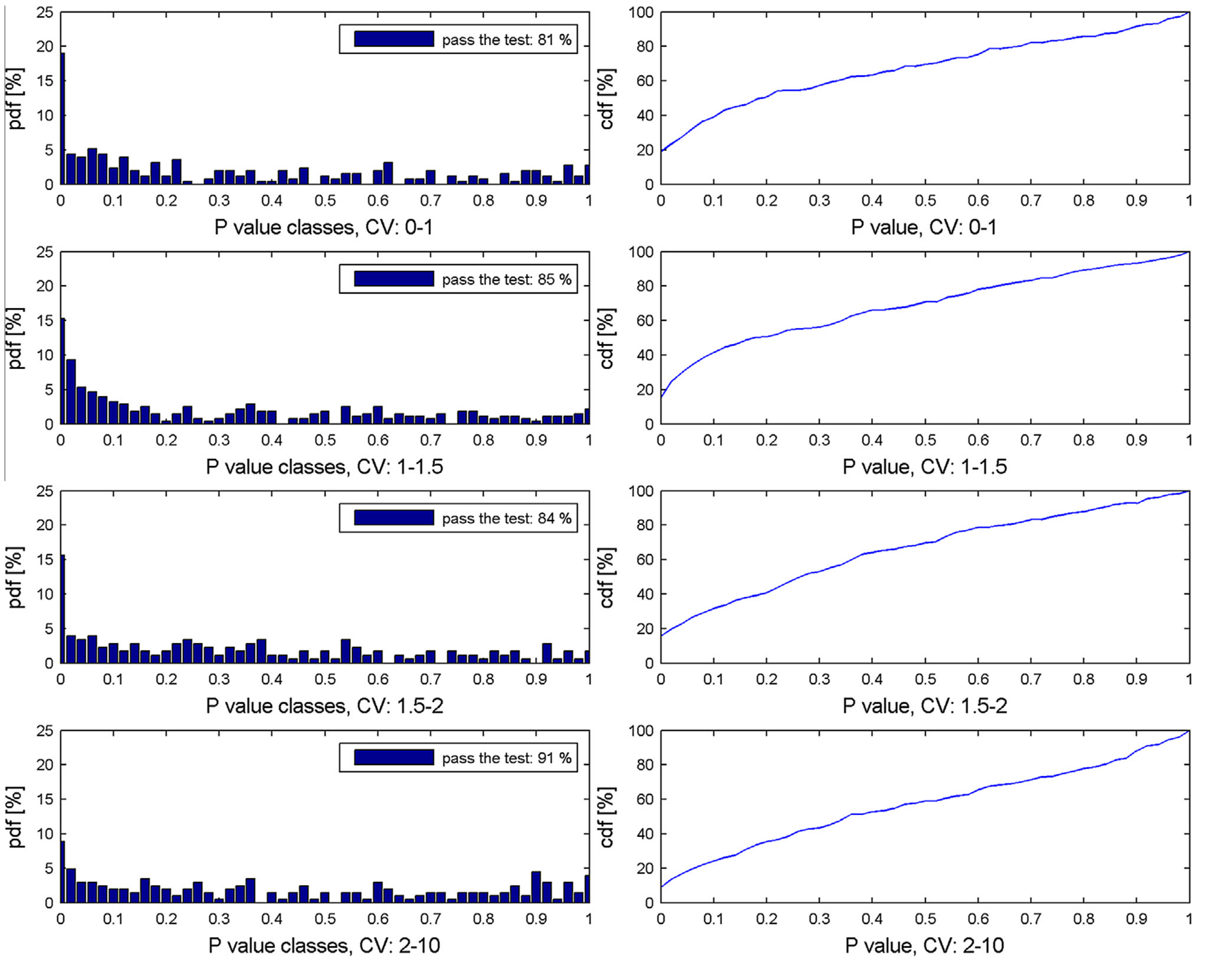

Fig. 20. The Kolmogorov–Smirnov test on AMSD. The results are presented in terms of the *P*-value and the percentage of stations that passed the test. Results are shown for different classes of CV. Left column panels: PDFs of the *P*-value. Right column panels: CDFs of the *P*-value.

Fig. 11 shows the good fit between the observed and generated duration curve, while Fig. 12 shows the results in terms of the hydrograph; the bottom panel demonstrates that the model produces good results even after the dam is built. This can be considered a good result when applying the method in non-stationary conditions (e.g., climate change).

In Fig. 13, a comparison between the StreamFARM simulation and the observation is reported for another test basin (Test basin 2) with different hydro-climatic characteristics with respect to Test basin 1. In this case, the semi-arid climate is likely the primary cause of the very low base flow, and the daily stream flow is strongly influenced by sub-monthly occurrences of rainfall events. This results in poorer model performance, with a modelled stream flow that has a larger range of variability with respect to the observed variability, and sub-monthly flow sequences that are sometimes far from the one that was observed. These results are confirmed by the values shown in Table 2, with negative values of NS for the hydrographs and larger values of the standard deviation for all scores with respect to the ones reported in Table 1.

4.2. Results of the complete dataset

The procedure of calibration and verification (1/3 of the length of the time series used for calibration) was applied to all of the available time series with lengths greater than 40 years. The procedure was applied using the following modality:

1. Calibration was conducted N ($N = 100$) times using the mean values of the parameters (see Section 3.2); and
2. Verification was carried out generating one possible downscaled stream flow history for each station.

A comparison between the observed and simulated data was made referring to both hydrographs and duration curves.

To show the results in a synthetic way, the graphs in Fig. 14 have been constructed using the results of all of the considered stations. The top panel represents the PDF of the NS between the observed and modelled duration curves. The bottom panel shows the Cumulative Density Function (CDF), which decreases with increasing x because NS tends to 1 for a perfect fit. Both graphs show that the model reproduces the observations well from a statistical point of view (duration curved), and more than the 90% of the 919 stations had a NS value larger than 0.95 (very good performance).

Graphs similar to those presented in Fig. 14 have been constructed for the hydrographs and are shown in Fig. 15. In this case, the results clearly perform less well because the downscaling procedure has no information about the real temporal history of the stream flow at the daily scale. StreamFARM can only generate a

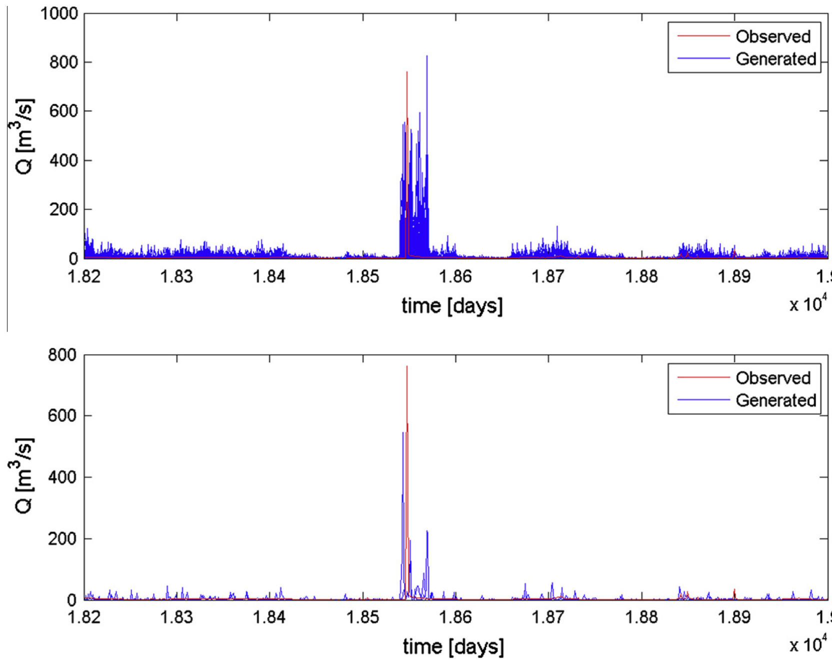

Fig. 21. Example of a daily stream flow time-series generated with StreamFARM for a flash flood regime basin. In the top panel, all of the members are shown while, in the bottom panel, a single member has been extracted and shown. The observed and generated hydrographs have similar characteristics (e.g., base flow and peak flows) but different temporal sequences.

possible time series without respect to the real sequence of peak event and recession curves and reproduces daily flow only from a statistically point of view. In spite of this, the results are satisfactory, and 60% of the stations have NS > 0.5.

Similar to Figs. 14 and 15, graphs demonstrating the relative error (RE) were constructed (Figs. 16 and 17).

In this case, the results are better for the duration curves because StrainFARM preserves the statistical characteristics of the daily time series, and more than 80% of the stations had RE < 0.1.

For the hydrographs, only 10% of the stations had RE < 0.1, and the peak PDF was for RE = 0.3.

The presented results demonstrate the global performance of the model on the entire dataset. As shown in Section 2, the considered basins belong to a wide range of environments, sizes, and different hydrological regimes; therefore, it is interesting to analyse the behaviour of the model for the different catchment types.

To do this, we referred to the CV as a synthetic indicator of the hydrological regime, and we considered 4 different classes:

- CV from 0 to 1, low variability of AMDS;
- CV from 1 to 1.5, medium variability of AMDS;
- CV from 1.5 to 2, high variability of AMDS; and
- CV larger than 2, very high variability of AMDS.

For these CV classes, the PDFs and CDFs of NS and RE were built with respect to the duration curves.

Both Figs. 18 and 19 demonstrate that the model performs less well when CV increases, confirming what was intuitively expected. High values of CV indicate that the hydro-climatic regime (arid and semi-arid) and the drainage area (small or medium) are such that the sub-monthly stream flow is often only poorly correlated with the monthly mean stream flow, as a consequence StreamFARM has greater difficulties reproducing daily values from the monthly total volume. Regardless, the results are discrete even for high CV values, with 80% of stations having NS values greater than 0.9 and RE < 0.3.

Basins with low CV show very good results. They have a more stable hydrologic regime likely due to a combination of various factors, such as a medium or large area, a regular rainfall regime, and, in some cases, the influence of melting snow that can contribute to maintaining a stable hydrological regime through the different seasons.

As a final analysis to evaluate the performance of the StreamFARM model, we analysed its ability to reproduce AMDS. Therefore, we executed the Kolmogorov–Smirnov test (KS-test) on each pair of observed and modelled AMSD series to determine if they belonged to the same statistical distribution. The test was performed with a 5% of significance level and furnished two outputs: the first is the binary decision if the two series are or are not from the same distribution and the second is the *P*-value, which is near 0 if the two series are from different distributions and near 1 if they are from the same distribution.

The results are presented in Fig. 20 for the aforementioned classes of CV. For each CV class, there is always a percentage of sections where the KS-test is not passed and the *P*-value is low, illustrating that StramFARM is unable to generate a correct distribution of AMSD in some situations. Contrary to what happens in the case of the analysis on hydrographs and duration curves, there is no degradation in the results with increasing CV values; for CV values in the range 1.5–2, 84% of the stations pass the test, and, for CV values larger than 2, 91% of the stations pass the test.

Therefore, in spite of the fact that in some conditions StreamFARM does not give very good results when describing all of the hydrological conditions of a station, it can return good results when reproducing some particular statistical properties (i.e., annual daily maxima).

5. Conclusions

In this study, we presented a downscaling algorithm that downscales monthly stream flows to daily stream flows. It performs a time disaggregation and, through the use of a stochastic term, can be used in ensemble or probabilistic mode to generate a number of possible daily time series. The algorithm has two parameters that can be calibrated to reproduce the duration curves for periods in which daily data are available and can then be applied in situations in which only monthly data are available.

The method was applied to a large dataset that covered all of North and Central America with good results in terms of reproducing duration curves and even modelling hydrographs. The considered stations have upstream drainage areas in the range of 10^3–10^6 km^2 and are located in zones that have different climatology (Peel et al., 2007). StreamFARM has therefore been applied to a variety of basins with a wide range of hydrologic regimes. The results highlight that the model performs better for basins with a low CV on AMDS (a catchment with temperate or cold climates) than those with a high CV on AMDS (a catchment with arid or semi-arid climates). Conversely, the results are both stable and good when the distribution of AMDS is considered as a term of comparison.

Possible limitations can arise for cases in which the maximum daily flow frequently occurs in a month where the maximum monthly flow occurs or when flood events are uncorrelated to the seasonal trend of flow volumes, that is, cases where snowmelt has strong effects on the monthly runoff volume or cases where small basins have flash flood regimes. In these cases, StreamFARM can partially compensate for the lack of information if it is well parameterized. The model will generate low frequent flows in periods that can be potentially different from reality; however, it will maintain the likely statistical and physical characteristics. In Fig. 21, we show an example of a basin in a flash flood regime; in the upper panel, the 100 ensemble members of the daily stream flow are shown, while in the lower panel, only 2 extracted members are shown. The time series generated with StreamFARM are reasonably realistic stream flow realizations for the considered basin (e.g., similar low flow values and peak flows); however, the temporal sequence is quite different from the observations, this is especially evident when analysing the peak flow events.

In the future, work can be performed regarding the parameterization of the model. A seasonal parameterization may reduce some of the limitations found in this first application. The possibility of adding a regional approach that relates basin morpho-climatic characteristics (such as Area, Slope, and Annual rainfall) to the model parameters could be investigated to apply the model when only monthly data are available, and it is not possible to carry out a calibration on a single station. This could be an interesting issue because it would allow the model to be applied to certain basins by exploiting the availability of data in other basins that have similar characteristics, climatology, and flow regimes. Another issue to investigate is the possibility of adapting the method to different time scales, for example, to downscale daily data to hourly data.

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References

Acharya, A., Ryu, J., 2014. Simple method for streamflow disaggregation. J. Hydrol. Eng. 19 (3), 509–519.
Hosking, J.R.M., Wallis, J.R., 1993. Some statistics useful in regional frequency analysis. Water Resour. Res. 29, 271–281.
Kottegoda, N.T., Rosso, R., 1997. Statistics, Probability and Reliability for Civil and Environmental Engineers. McGraw-Hill.
Koutsoyiannis, D., 2001. Coupling stochastic models of different timescales. Water Resour. Res. 37 (2), 379–391.
Koutsoyiannis, D., Manetas, A., 1996. Simple disaggregation by accurate adjusting procedures. Water Resour. Res. 32 (7), 2105–2117.
Kumar, D.N., Lall, U., Peterson, M.R., 2000. Multisite disaggregation of monthly to daily streamflow. Water Resour. Res. 36 (7), 1823–1833.
Lall, U., Sharma, A., 1996. A nearest neighbor bootstrap for resampling hydrologic time series. Water Resour. Res. 32 (3), 679–693.
Lane, W.L., 1979. Applied Stochastic Techniques Users Manual. Eng. And Res. Cent., Bur. of Reclam., Denver, Colo.
Maidment, D., 1992. Handbook of Hydrology. McGraw-Hill, Inc.
Nash, J.E., Sutcliffe, J.V., 1970. River flood forecasting through conceptual models I: a discussion of principles. J. Hydrol. 10, 282–290.
Peel, M.C., Finlayson, B.L., McMahon, T.A., 2007. Updated world map of the Koppen–Geiger climate classification. Hydrol. Earth Syst. Sci. 11, 1633–1644.
Prairie, J., Rajagopalan, B., Lall, U., Fulp, T., 2007. A stochastic nonparametric technique for space-time disaggregation of streamflows. Water Resour. Res. 43, W03432. http://dx.doi.org/10.1029/2005WR004721.
Rajagopalan, B., Lall, U., 1999. A k-nearest-neighbor simulator for daily precipitation and other weather variables. Water Resour. Res. 35 (10), 3089–3101.
Rebora, N., Ferraris, L., von Hardenberg, J., Provenzale, A., 2006. Rainfall downscaling and flood forecasting: a case study in the Mediterranean area. Nat. Hazards Earth Syst. Sci. 6, 611–619.
Rebora, N., Ferraris, L., von Hardenberg, J., Provenzale, A., 2006. The RainFARM: rainfall downscaling by a filtered auto regressive model. J. Hydrometeorol. 7 (4), 724–738.
Salas, J.D., Delleur, J.W., Yevjevich, V., Lane, W.L., 1980. Applied Modeling of Hydrologic Time Series. Water Resour. Publ., Highlands Ranch, Colo. (pp. 484).
Smakhtin, V.U., 1999. Restoration of natural daily flow time-series in regulated rivers using non-linear spatial interpolation technique. Regul. Rivers Res. Manage. 15, 311–323.
Smakhtin, V.U., 2000. Estimating daily flow duration curves from monthly streamflow data. Water SA 26 (1) [ISSN 0378-4738].
Tarboton, D.G., Sharma, A., Lall, U., 1998. Disaggregation procedures for stochastic hydrology based on nonparametric density estimation. Water Resour. Res. 34 (1), 107–119.
von Hardenberg, J., Rebora, N., Ferraris, L., Provenzale, A., 2007. Meteorological uncertainty and rainfall downscaling. Nonlin. Process. Geophys. 14, 193–199.
Yates, D., Gangopadhyay, S., Rajagopalan, B., Strzepek, K., 2003. A technique for generating regional climate scenarios using a nearest neighbour bootstrap. Water Resour. Res. 39 (7), 1199. http://dx.doi.org/10.1029/2002WR001769.