

1 **Analysis of the streamflow extremes and long term water balance**
2 **in Liguria Region of Italy using a cloud permitting grid spacing**
3 **reanalysis dataset**

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8 **Abstract**

9 Characterizing the hydrometeorological extremes, both in terms of rainfall and streamflow,
10 as well as the estimation of long term water balance indicators are essential issues for the
11 flood alert and water management services. In recent years simulations carried out with
12 meteorological models are getting available at increasing spatial and temporal resolutions
13 (both historical reanalysis and near real-time hindcast studies); these meteorological datasets
14 can thus be used as input in distributed hydrological models to drive long-period hydrological
15 reanalysis. In this work we adopted a high resolution meteorological reanalysis dataset that
16 covers the whole Europe territory for the period between 1979 and 2008, with 4 km grid
17 spacing and 3 hours of time resolution. This reanalysis dataset was used together with a
18 rainfall downscaling algorithm and a rainfall bias correction technique in order to produce
19 input to a continuous and distributed hydrological model. The resulting modelling chain
20 allowed to produce long time series of distributed hydrological variables, inter alia
21 streamflows and evapotranspiration, in the Liguria Region, located in the Northern part of
22 Italy, and among the western Mediterranean areas mostly impacted by severe hydro-
23 meteorological events.

24 The observations available from the local rain gauges network were compared with the
25 rainfall estimated by the dataset, and then used to perform a bias correction with the aim of
26 matching the observed climatology. An analysis of the annual maxima discharges derived by

1 simulated streamflow time series was carried out, by comparing them with observed
2 discharge where available and using as benchmark a regional statistical analyses elsewhere.
3 Eventually, an investigation of long term water balance was performed by comparing
4 simulated runoff ratios with available estimations based on observations.

5 The study highlights both limits and potentialities of the considered framework as a
6 methodological approach to undertake hydrological analysis in study areas mainly
7 characterized by small basins, thus allowing to overcome the limits of observations which are
8 punctual and in some cases not fully reliable.

9 **1 Introduction**

10 The estimation of the magnitude and the probability of occurrence of a certain streamflow is
11 an important task for a number of purposes: risk assessment, design of structural protections
12 against flooding, civil protection aims, settings of thresholds in early warning systems.

13 The standard approach of using streamflow observations to carry out a statistical analysis on a
14 particular outlet (Kottegoda and Rosso, 1997), is not always possible because of lack of
15 observations; to solve this problem a frequency regionalization approach can be used (De
16 Michele and Rosso, 2002) even using both observations and streamflow derived by
17 hydrological modelling (Boni et al., 2007).

18 On the other hand studies and methodologies regarding the management of water resources
19 and drought also have an important role especially in the perspective of possible future
20 changes in climate and water needs (Calanca et al., 2006; Fu et al., 2007; Döll and Müller,
21 2012; Asadieh and Krakauer, 2017). In this case the analysis of long-term water balance
22 components is of primary importance, and the evaluation of total runoff and
23 evapotranspiration becomes crucial.

24 In the last decades the use of Reanalysis of past weather for hydrological purposes and to
25 study basins behaviour in different hydrological regimes became quite frequent, also because

1 the reliability of reanalysis meteorological variables is constantly improving together with the
2 increasing of spatial and temporal resolution. Among many others, Choi et al. (2008)
3 investigated the applicability of temperature and precipitation data from the North American
4 Regional Reanalysis (NARR, about 32 km grid spacing) for hydrological modelling of
5 selected watersheds in northern Manitoba, while Bastola and Misra (2013) used reanalysis
6 products as surrogates for large-scale observations and showed that they are superior in
7 simulating hydrological response in respect to other four considered meteorological datasets.
8 Furthermore, Krog et al. (2015) used ECMWF interim reanalysis (ERA-Interim, about 70 km
9 grid spacing) as input to an hydrological model in order to better understand the processes
10 that drive the hydrological response of one of the largest rivers in Patagonia; similarly,
11 Nkiaka et al. (2017) investigated the potential of using global reanalysis datasets as input for
12 hydrological modelling in the data-scarce Sudan-Sahel region.

13 In this work a high-resolution ($\Delta t=3$ h, $\Delta x=4$ km) regional dynamical downscaling of
14 historical climate scenarios is used as input to a hydro-meteorological chain including a
15 rainfall downscaling algorithm (RainFARM, Rebora et al. 2006a, 2006b) and a continuous
16 distributed hydrological model (Continuum, Silvestro et al. 2013), producing high-resolution
17 ($\Delta t=1$ h, $\Delta x=< 500$ m) 30 years length modelled variables history for a reference
18 Mediterranean region. Both Continuum model and RainFARM downscaling algorithm were
19 widely employed and tested in the study area in previous works (Gabellani et al., 2008;
20 Silvestro et al., 2014; Laiolo et al., 2015; Davolio et al., 2017).

21 The CORDEX (COordinated Regional climate Downscaling Experiment, Giorgi et al. 2009)
22 initiative is aiming at producing regional climate change projections worldwide for input into
23 impact, adaptation and disaster risk reduction studies using regional climate models (RCM) at
24 fine spatio-temporal resolution and forced by different GCMs from the CMIP5 (Coupled
25 Model Intercomparison Project Phase 5, CMIP5) archive. Along these lines Kotlarski et al.

1 (2014) confirmed, with simulations on grid-resolutions up to about 12 km (0.11°), the
2 capability of RCMs to correctly reproduce the main features of the European climate for the
3 period 1979-2008. However they also exhibit relevant modeling errors concerning some
4 metrics, certain regions and seasons: as an example precipitation biases are in the $\pm 40\%$ range
5 while seasonally and regionally averaged temperature biases are generally smaller than 1.5
6 °C. Building on these findings, Pieri et al. (2015) moved one step further, in the framework of
7 the EXtreme PREcipitation and Hydrological climate Scenario Simulations (EXPRESS-
8 Hydro) project, by dynamically downscaling, at 4 km grid spacing and 3 hours time
9 resolution, the historical climate scenarios generated by the ERA-Interim reanalysis using the
10 state-of-the-art non-hydrostatic Weather Research and Forecasting (WRF) regional climate
11 model.

12 The distributed nature of the state and output variables of the hydrological model allowed to
13 investigate the possibility of using this kind of modelling chain for extreme streamflow
14 statistical analysis (e.g. distribution of annual discharge maxima) and long term water balance
15 (e.g. long term runoff ratio) in a fully distributed perspective. Furthermore, the high spatial
16 grid spacing and time resolution of the forcings, together with the use of a rainfall
17 downscaling model, allowed to explore the use of such high resolution reanalysis in regions
18 characterized by the presence of small hydrological watersheds (Silvestro et al., 2011) in areas
19 with complex topography and frequently stroke by flash floods (Altinbilek et al., 1997;
20 Cassola et al., 2016). These latter, together with the analysis of the distribution of flood
21 extremes, are the main novel contributions of the presented analysis in respect to other works
22 that employ a similar modelling cascade. It is in fact mandatory using high resolution
23 reanalysis since coarser ones can not reproduce the small-scale rainfall structures needed to
24 correctly reproduce the hydrometeorology processes of the study region.

1 The study shows the capabilities and the limits of the considered modelling chain to
2 reproduce low frequency streamflow and long term water balance as an alternative to the use
3 of observations, in a scarce data environment or in those cases where the spatial distribution
4 of hydro-meteorological processes results to be essential.

5 The manuscript is organized as follows: section 2 describes the study area, hydro-
6 meteorological data set and models, section 3 shows the results, and in section 4 the
7 discussion and conclusions are reported.

8 **2 Materials and Methods**

9 **2.1 Study Area and Case study**

10 Liguria Region is located in northern Italy (Figure 1), it is characterized by basins which have
11 steep valleys due to their proximity to the Apennines and Alps and drainage area in the range
12 10^1 to 10^3 km². The response time to precipitation pulses of these basins is short, ranging
13 between 0.5 to 10 hours (Maidment, 1992; Giannoni et al., 2005). The maximum elevation of
14 mountains is around 2500 m, valleys have very steep slopes, with average values at basin
15 scale between 10 and 20 % ; a large part of the ground surface of the region is covered with
16 forest or other types of vegetation like meadows and shrubs with the catchments mouth often
17 in correspondence of towns and cities densely inhabited. The hydrological regime is
18 prevalently torrential and the entire study area is frequently stroke by flash floods (Rebora et
19 al., 2013), as a consequence the variability of annual discharge maxima is high. Winter
20 seasons are generally not rigid but the elevation varies from sea level to more than 2000 m, as
21 consequences temperatures are below zero only few days/year along the coast and at low
22 altitude but they drops even below -10 °C inland; during warm season temperature rises rarely
23 over 31-32 °C. Snow occurs only few days during the year and it is not infrequent that near
24 the coast it does not snow for several consecutive years.

1 A quite dense meteorological stations network monitors the territory of Liguria, it is named
2 OMIRL – “Osservatorio Meteo-Idrologico della Regione Liguria” and it is managed by the
3 Environmental Agency of Liguria Region (ARPAL). This monitoring network yields
4 raingauge measurements with timesteps smaller than 1 hour (e.g. 5-10 minutes) for more than
5 150 gauges over the region; the density is averagely 1 raingauge/40 km². Temperature,
6 radiation, wind, air humidity gauges are part of the system, even though their density is lower
7 than the rain gauges one. Continuous data were collected from 2011 to 2014 for
8 calibrating/validating the hydrological model. For a subset of 95 raingauge stations (see
9 Figure 1), historical validated data are available from 1978 to 2010 at daily scale; in fact
10 ARPAL built a database useful for climatic and statistical analysis which is freely available
11 on web ([http://www.arpal.gov.it/homepage/meteo/analisi-climatologiche/atlante-climatico-](http://www.arpal.gov.it/homepage/meteo/analisi-climatologiche/atlante-climatico-della-liguria.html)
12 [della-liguria.html](http://www.arpal.gov.it/homepage/meteo/analisi-climatologiche/atlante-climatico-della-liguria.html)). These data were used in the presented study for bias correction of
13 reanalysis rainfall estimation.

14 For 11 level gauge stations continuous hourly data are available from 2011 to 2014 together
15 with stage discharge curves, while annual discharge maxima (hereafter ADM) time series
16 longer than 30 yrs are available for a set of 15 level gauges (Figure 1); these latter cover sub-
17 periods which are not continuous from 1950 to recent years. Moreover, in the Hydrologic
18 Annual Survey ([http://www.arpal.gov.it/homepage/meteo/pubblicazioni/annali-](http://www.arpal.gov.it/homepage/meteo/pubblicazioni/annali-idrologici.html)
19 [idrologici.html](http://www.arpal.gov.it/homepage/meteo/pubblicazioni/annali-idrologici.html)), an official document published by the Regional Agency for Environment
20 Protection, annual basin-scale runoff ratio (defined as runoff volume/precipitation) are
21 available for 6 stations.

22 In Table 1 the availability of the discharge and discharge-related data is summarized together
23 with hydro-geomorphic characteristics of the basins upstream each station.

24 All the described data are checked by ARPAL personnel in agreement with WMO
25 recommendations to keep out measuring errors and evidently not valid values.

1 **2.2 EXPRESS-Hydro reanalysis**

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3 Pieri et al. (2015) assessed the WRF regional climate model performances to reproduce
4 observed precipitation extremes, over Europe and with a particular focus on the Greater
5 Alpine Region; the assessment was performed by comparing the simulations results with
6 available gridded observational datasets such as the high-resolution Alpine precipitation grid
7 dataset (APGD) developed by MeteoSwiss in the framework of the European Reanalysis and
8 Observations for Monitoring (EURO4M) collaborative project (Isotta et al. 2013). Overall
9 Pieri et al. (2015) results showed that increased grid spacing together with the use of
10 explicitly resolved convection allows to achieve a better modelling of the precipitation field
11 spatio-temporal distribution. Furthermore, the overestimation of precipitation (around 5% on
12 annual average over the European domain with respect to E-OBS observational data) was
13 reduced significantly and the distribution and the statistics of the rainfall rate, particularly
14 over the Alps and Apennines area, were better reproduced. More recent studies confirmed the
15 need for high-resolution dynamical downscaling for extreme weather impact studies in
16 regions with complex terrain (Pontoppidan et al. 2017, Schwitalla et al. 2017).

17 In this work we extended the analysis of average annual and seasonal high-resolution rainfall
18 reanalysis for Liguria area, taking advantage of the richer climatological dataset (95 stations):
19 results and comments are provided in section 3.1.

20 **2.3 Bias correction of rainfall fields (B.C.)**

21 Before being used as input for the hydrological simulations, the EXPRESS-Hydro reanalysis
22 rainfall dataset was compared with the climatological precipitation data obtained by the
23 Liguria raingauge dataset (Liguria climatological atlas). The observed dataset is constituted
24 by validated time series of about 95 raingauges homogeneously distributed on the Liguria

1 Region territory: the time series cover the whole 1979-2008 period of the EXPRESS-Hydro
2 dataset (even if not for all gauges) at daily timestep.

3 In order to provide to the hydrological model Continuum the most reliable input data possible,
4 the EXPRESS-Hydro reanalysis precipitation data were BIAS-corrected by employing the
5 observed data to assure an accurate reproduction of the rainfall climatology of the area in
6 terms of monthly cumulate. No other variables were available in the Liguria climatological
7 atlas, so no BIAS correction was applied to other variables of the EXPRESS-Hydro dataset.

8 Different methods are available in literature to perform a BIAS correction (hereafter B.C.) on
9 different variables (rainfall, temperature, etc., Fang et al. 2015): in this work a CDF-matching
10 approach was selected (Fang et al. 2015).

11 Given the analysis performed on the EXPRESS-Hydro reanalysis dataset (see Section 3.1),
12 and the statistical analysis of the observed data (Liguria climatological atlas) it was evident
13 that a strong seasonality is present in both datasets.

14 In order to preserve both the seasonality and the inter-annual variability of the observations,
15 the correction was based on the monthly cumulates, that were computed for both the Express-
16 Hydro dataset (thus producing $N \times 12$ maps representing the average cumulate rainfall map
17 for each month, N number of years of the Express-Hydro dataset) and the observed dataset
18 (producing time series of $N_{\text{obs}} \times 12$ values representing the average accumulated rainfall for
19 each month and for each of the available raingauges, N_{obs} number of years of the observed
20 dataset).

21 To allow a direct comparison between the observed data and the modeled dataset, the monthly
22 cumulated data from the raingauges were previously interpolated on the Express-Hydro
23 spatial grid, by using a kriging technique with a Spherical variogram. No regression with
24 other spatialized variables (e.g. elevation) was employed because previous tests showed that
25 no significant correlation were present. Since the density of the rain gauge network is high

1 and considering the fact that the interpolation was employed only for the monthly cumulates,
 2 the possible errors introduced by the interpolation can be considered acceptable. In fact, the
 3 spatial and temporal structures of the rainfall events of interest (short-period and spatially
 4 concentrated, see previous Sections and Boni et al. (2007)) are not significantly altered.

5 For each cell i , the empirical CDF (Cumulative Distribution Function) of observed and
 6 modeled values were computed. At the purpose of minimizing distortions of the information,
 7 these CDFs were computed separately for each month of the year (January, February, etc.).

8 In the CDF-matching process the observations CDF was imposed to the Expresss-Hydro time
 9 series of a given cell i in order to obtain the corrected time series of the monthly cumulate:

$$10 \quad PM'_{i,m} = F_{OSS,i}^{-1}(F_{MOD,i}(PM_{i,m})) \quad (1)$$

11 where PM is the Express-Hydro monthly cumulate rainfall, PM' is the bias-corrected
 12 monthly cumulate rainfall, m is the index of the month of the original series, $F_{MOD,i}$ and $F_{OSS,i}$
 13 are respectively the CDF of the modeled and observed monthly rainfalls in the cell i .

14 Given these corrected monthly time series, the single instantaneous value of rainfall p
 15 (3-hours cumulate) was corrected as follows:

$$16 \quad p'_{i,t} = p_{i,t} \frac{PM'_{i,m}}{PM_{i,m}} \quad (2)$$

17 where:

- 18 - $p_{i,t}$ is the 3-hours cumulate rainfall modeled in the cell i at instant t
- 19 - $p'_{i,t}$ is the bias-corrected 3-hours cumulate rainfall modeled in the cell i at instant t
- 20 - $PM_{i,m}$ is the monthly cumulate rainfall modeled in the cell i in month m (in which the
 21 instant t falls)
- 22 - $PM'_{i,m}$ is the monthly cumulate rainfall modeled in the cell i in month m (in which the
 23 instant t falls) corrected with the CDF-matching

24 The described procedure allowed obtaining a 3-hours maps dataset in which the model bias
 25 was eliminated by keeping the characteristics of the model in terms of seasonality and inter-

1 annual variability. Furthermore, the procedure design allows to avoid alterations of possible
2 temporal trends, at both domain and cell spatial scale.

3 **2.4 Downscaling the rainfall with RainFARM Model**

4 RainFARM (Rebora et al. 2006a, 2006b) is a mathematical model able to downscale rainfall
5 fields that can be exploited for generating rainfall scenarios consistent with large scale
6 forecasts done by the Numerical Weather Prediction Systems (NWPS) as in Laiolo et al.
7 (2013) and/or by expert forecasters (Silvestro and Rebora, 2014). The model accounts for the
8 variability of precipitation fields at small spatial and time scales (e.g. $L \leq 1$ km, $t \leq 1$ hour),
9 preserving the precipitation volume at those scales where quantitative precipitation forecasts
10 are considered reliable (L_r , t_r). RainFARM is able on one side to preserve spatial and time
11 patterns at L_r , t_r , on the other side to produce small-scale structures of rainfall which are
12 consistent with detailed remote sensor observations as meteorological-radar estimation.

13 In the model the spatial-temporal Fourier spectrum of the precipitation field is estimated using
14 rainfall fields predicted by a meteorological model and it is mathematically described as
15 follows:

$$16 \quad \left| \hat{g}(k_x, k_y, \omega) \right|^2 \propto (k_x^2 + k_y^2)^{-\alpha/2} \omega^{-\beta} \quad (3)$$

17 k_x and k_y are the x and y spatial wavenumbers, ω the temporal wavenumber (frequency),
18 while α and β are two parameters that are calibrated fitting the power spectrum of rainfall
19 derived by a NWPS on the frequencies that correspond to the spatial-time scales L_r and t_r .
20 Extending the spectrum defined by equation (3) to the larger wave numbers/frequencies it is
21 possible to generate a spatial-time rainfall field at a high resolution (Rebora et al. 2006b).
22 Since the Fourier phases related with the power spectrum (3) are randomly generated before
23 the backwards transformation in real space, RainFARM can give as output an ensemble of

1 equi-probable high-resolution fields that remain coherent at large scale with the rainfall
2 forecast done by NWPS. RainFARM was designed to be used for flood forecast systems
3 implemented on small and medium sized basins (drainage area $< 10^3\text{-}10^4 \text{ km}^2$) and it was
4 tested in various works on the study area (Rebora et al., 2006a; Silvestro et al. 2012; Silvestro
5 and Rebora, 2014)

6 In this study the algorithm is used to downscale the bias-corrected EXPRESS-Hydro
7 reanalysis; the reliable spatial and time scales are assumed as the nominal grid spacing and
8 temporal resolution of EXPRESS-Hydro precipitation (4 km and 3 hours, Hardenberg et al.
9 2015 and Pieri et al. 2015). The downscaling algorithm is not used in probabilistic
10 configuration, but to build a possible rainfall time-spatial pattern at 1 km and 1 hour
11 resolution that is compatible with the runoff formation at small scales, since most of the
12 catchments in the proposed study area have reduced dimensions (often $<100\text{-}200 \text{ km}^2$) with
13 response time in the order of 1-6 hours.

14 **2.5 The hydrological model: Continuum**

15 The hydrological model used in this study is *Continuum* (Silvestro et al. 2013), it is a
16 distributed and continuous model that relies on a space-filling approach, and uses a
17 consolidated way for the identification of the drainage network components (Giannoni et al.,
18 2005). All of the main hydrological processes are mathematically described in a distributed
19 way in Continuum but it was designed to be a balance solution between complex physically
20 based models (which describe the physical phenomena with high detail often introducing
21 complex parameterization) and models with a empirical approach (easy to implement but far
22 from reality) (Silvestro et al., 2015). The basin or domain of interest is represented through a
23 regular grid, derived by a Digital Elevation Model (DEM) while the flow directions are
24 defined with an algorithm that calculates the directions of maximum slope using the DEM.
25 An algorithm classifies each cell of the drainage network as hillslope or channel flow

1 depending on the main flow regime; a morphologic filter defined by the expression $AS^k = C$ is
2 used to distinguish between hillslopes and channels ; A is the drainage area upstream of each
3 cell [L^2], S is the local slope [-], k and C are constants related to the geomorphology of the
4 catchment (Giannoni et al., 2000). The surface flow scheme treats differently channel and
5 hillslope flows: the overland flow (hillslopes) is described by a linear reservoir
6 schematization, while an approach derived by kinematic wave (Wooding, 1965; Todini and
7 Ciarapica, 2001) is used for modeling the channel flow.

8 Subsurface flows and infiltration are modeled using a methodology based on an adaptation of
9 the Horton equations (Bauer, 1974; Disikin and Nazimov, 1997); it accounts for soil moisture
10 evolution even in conditions of intermittent and low-intensity rainfall as described in
11 Gabellani et al., (2008).

12 Interception of vegetation is schematized with a reservoir that has a retention capacity S_v ; this
13 latter is estimated using static informative layers of vegetation type or Leaf Area Index data;
14 the flow in deep soil and the water table evolution are modeled with a distributed linear
15 reservoir schematization and a simplified version of Darcy equation.

16 The energy balance uses the “force restore equation” (Dickinson, 1988) that allows to
17 explicitly model the soil surface temperature.

18 Snow melting and accumulation is simulated with simple equations forced with air
19 temperature and solar radiation (Maidment, 1992) as described in Silvestro et al. (2015).

20 Continuum needs as input the following variables: rainfall, air temperature, short-wave solar
21 radiation, wind velocity, air relative humidity. When the ExpressHYDRO reanalysis are used
22 as input the following variables are considered: 2 m temperature, 10 m wind, rain depth,
23 downward short wave flux at ground surface, 2 m air relative humidity

24 The parameters that require calibration in Continuum model are six, they are often estimated
25 at basin or sub-basin scale: two for the surface flow ($u_h [m^{0.5}s^{-1}]$ and $u_c [s^{-1}]$), two for the sub-

1 surface flow (c_t [-] and c_f [-]) and two for deep flow and watertable (V_{Wmax} [mm] and R_f [-])
2 processes.

3 The parameter u_h affects those hydrograph components which are related to fast surface flow
4 as well as u_c but the impact of this latter depends on the length of the channeled paths. c_f is
5 related to saturated hydraulic conductivity and controls the rate of subsurface flow rate (i.e.,
6 it). c_t identifies the part of water volume in the soil that can be extracted through
7 evapotranspiration only and is thus related to the soil field capacity, while both c_t and c_f
8 regulate the dynamics of saturation of the root-zone. The two parameters V_{Wmax} and R_f rule
9 the flow in the deep soil and the dynamic of watertable, they impact on recession curves and
10 have certain influence on flood hydrographs, only when catchments of large drainage area are
11 considered (Silvestro et al., 2013).

12 In the presented work, Continuum was implemented with a time resolution of 60 min and
13 with a spatial resolution of 0.005 deg (about 480 m). The Shuttle Radar Topographic Mission
14 (SRTM) DEM was employed.

15 It was possible to calibrate the model for 11 sections where streamflow observations are
16 available; ground stations measurements were interpolated on a regular grid of 1 km
17 resolution by using Kriging method and used as input to the model. 01/01/2013-31/12/2014
18 was used as validation period, and the following skill scores, used also in the calibration
19 process, were employed to measure the model performances.

20 The Nash Sutcliffe (NS) coefficient (Nash and Sutcliffe, 1970):

$$21 \quad NS = 1 - \frac{\sum_{t=1}^{t_{\max}} (Q_m(t) - Q_o(t))^2}{\sum_{t=1}^{t_{\max}} (Q_m(t) - \overline{Q_o})^2} \quad (4)$$

22 where $Q_m(t)$ and $Q_o(t)$ are the modelled and observed streamflows at time t . $\overline{Q_o}$ is the mean
23 observed streamflow.

1 Relative Error of High Flows (REHF)

$$2 \quad REHF = \frac{1}{t \max} \left[\sum_{t=1}^{t \max} \frac{|Q_m(t) - Q_o(t)|}{Q_o(t)} \right]_{Q > Q_{th}} \quad (5)$$

3 where Q_{th} is chosen as the 99 percentile of the observed hydrograph along the calibration
4 period. While NS has the purpose of evaluating the general reproduction of streamflow,
5 REHF score has the aim of giving high weight to high flows leading the calibration to better
6 reproduce the flood events.

7 NS and REHF were combined in a multi-objective function to carry out the calibration using
8 the approach proposed in Madsen (2000). Calibration was done analyzing the parameter space
9 using a brute force approach on 2011-2013 period in order to find the parameter set that
10 optimize the multi-objective function. Hourly streamflow data were used, while Curve
11 Number map was derived by the CORINE Land Cover
12 (<http://www.sinanet.isprambiente.it/it/progetti/corine-land-cover-1>). The final setting is
13 similar to the one described in Davolio et al. (2017).

14 The values of the skill scores were calculated for the validation period and resulted to be
15 satisfactory; they are reported in Table 2.

16 In those basins where it was not possible to make the calibration, average values of the
17 parameters obtained by the calibration process are assumed (see Table 2). The optimal
18 condition would be to have the chance of calibrating the model in all the study region but this
19 was not possible for lack of data. However, the employed hydrological model (as well as
20 similar models developed for working on same study area) demonstrated to well work in the
21 study environment (Giannoni et al., 2000, 2005; Gabellani et al., 2008; Silvestro et al. 2013,
22 2015, Cenci et al 2016) giving reasonable and quite reliable results also for not calibrated
23 sections when used for flood forecast aims (Regione Marche, 2016). This is valid when the
24 basins have similar characteristics especially regarding the surface response to intense rainfall

1 events and the main genesis of rainfall-runoff process; as a consequence, the parameters have
2 often similar values moving from a catchment to another. This was also the approach adopted
3 in Boni et al. (2007).

4 In order to have reduced warm up impacts on the 1979 (first year of EXPRESS-Hydro)
5 simulation a first run was done starting from a predefined initial condition and the state
6 variables simulated on the 31 of December of every year (from 1979 to 2008) were averaged
7 to estimate a reasonable initial condition for 1th January 1979 to be used in the final
8 simulation.

9 Once the run of hydrological model for the period 1979-2008 was done, we had available a
10 streamflow time series for each pixel of the calculation domain; ideally this is equivalent to
11 having a sort of gauge every Δx along the stream network. Since the spatial resolution of the
12 hydrological model is 480 m we discarded the analysis for basins with area smaller than
13 $A_{th}=15 \text{ km}^2$, because we believe that the surface water motion processes are not modeled with
14 a sufficient detail; $A_{th}=15 \text{ km}^2$ means a number of pixel around 60-70 to represent the
15 catchment and at least some cells classified as channel (Giannoni et al., 2005).

16 **2.6 Distribution of the annual discharge maxima**

17 The results of the modeling chain were firstly compared with observations using a typical
18 station-wise comparison approach: 15 gauge stations with at least 30 years of annual
19 discharge maxima were identified along the Ligurian territory from the eastern side to the
20 western one.

21 It was not possible to ensure a perfect overlapping between the simulation period and the
22 observed data availability, in many cases observed data are not temporally continuous and
23 they may cover longer periods (in some case 50-60 years) with large time windows of missing
24 data. However on the basis of the conclusions drawn in the framework of Liguria

1 climatological atlas, major climate change related trends for temperature, precipitation, and so
2 forth are not evident, thus supporting the database usage despite these data gaps.
3 The comparison between observed and reanalysis driven annual discharge maxima (ADM) is
4 firstly based on the analysis of the respective cumulative density function distributions.
5 The reanalysis driven ADM were fitted with a General Extreme Value (GEV) distribution
6 (see e.g., Hoskin and Wallis, 1993; Piras et al., 2015) that represents a good compromise
7 between flexibility and robustness. Other works based extreme statistical analysis on the Two
8 Components Extreme Value (TCEV) model (Rossi et al., 1984), nevertheless we decided to
9 use GEV since it has a smaller number of parameters and it was successfully applied for a
10 wide number of applications (CIMA Research Foundation, 2015; Piras et al., 2015).

11 **2.7 Regional analysis of the annual discharge maxima**

12 In order to carry out a comparison following a distributed approach we referred to the work
13 done in Boni et al. (2007) which is one of the methods operationally used in Liguria Region
14 (by public authorities and private engineer) to estimate the ADM quantiles (Provincial
15 Authority of Genoa, 2001; Silvestro et al., 2012). The method was conceived and tested
16 especially for the Tyrrhenian catchments of Liguria Region, so the presented analysis was
17 carried out only for this area. The method defines a hierarchical approach based on the
18 analysis of the non-dimensional random variable $X_0 = X/\mu_x$, obtained by grouping together all
19 available data, and making them non-dimensional with respect to each local (gauging station)
20 sample mean, μ_x , taken as the index flood for gauged sites. Index flood is estimated even
21 where observations were not available with support of rainfall regional frequency analysis and
22 rainfall-runoff modelling in order to allow quantile estimation in each point of the region.
23 The final result is a methodology to estimate the index flood that can be formalized as it
24 follows:

1 $Q_{index} = f(Area, longitude)$ (6)

2 While the quantile is:

3 $Q(T) = K(T) \cdot Q_{index}$ (7)

4 where T is the return period and K(T) is defined by the non-dimensional regional growth
5 curve. Boni et al. 2007 defined a unique K(T) applicable to all the studied region.

6 In the case of the modelling chain analyzed in this work there is the availability of a large
7 number of reanalysis driven time series because we can pick the 30 years long ADM series
8 for each pixel of the model grid where drainage area is larger than A_{th} . In practice, the fact
9 that we are using a distributed hydrological model, on one side allows the index flood
10 estimation as a simple mean of a time series in each point of the domain, on the other side
11 provides a large number of data to build the non-dimensional regional curve.

12 **3 Results**

13 **3.1 Precipitation analysis**

14 The comparison between precipitation climatology over Liguria from observational data and
15 Pieri et al (2015) results has been undertaken at the annual and seasonal scales.

16 Pieri et al. (2015), using EURO4M-APGD reference observational dataset (Isotta et al. 2013,
17 with about 50 daily raingauge stations over Liguria), already showed an overall
18 underestimation of the WRF rainfall depths on annual basis in Liguria, more evident on the
19 eastern side of the region (Figure 3, panels e-f of Pieri et al. 2015), with differences in the
20 range between -2 and -1 mm on the coastal eastern Liguria portion and between -1 and 0
21 mm/day on the eastern Appennine side.

22 The same analysis was repeated in this study, using 95 raingauge stations over Liguria: the
23 total annual rainfall depth results are largely confirmed both on eastern and western Liguria
24 sides (Figure 2).

1 Concerning the seasonal temporal scales results, EXPRESS-Hydro tends to underestimate
2 average observed rainfall depths during DJF (Figure 3) on eastern Liguria portion (between -1
3 and 0 mm/d) while overall it overestimates them on central-western Liguria (0-1 mm/d).
4 Similar argument holds also for the MAM period (Figure 3), even if the EXPRESS-Hydro
5 overestimation tends to get larger on the western side. During the JJA period (Figure 3),
6 instead, EXPRESS-Hydro exhibits an overestimation of observed average rainfall depths
7 between 0 and 1 mm/d over the western and eastern sides, while it is increasing to 1-2
8 mm/day over central Liguria. The underestimation gets worse over eastern Liguria during
9 SON (Figure 3), with values between -2 and -1 mm/d over the inland portions and up to -3
10 and -2 mm/d over the coastal one. Conversely, on the rest of the region the underestimation
11 falls between -1 and 0 mm/d. In Figure 4 the comparison between observations and
12 EXPRESS-Hydro at seasonal scale is also presented in terms of scatter plots exhibiting a good
13 correlation between reanalysis and observations, while in Table 3 we reported the BIAS and
14 the Root Mean Square Error (RMSE).

15 Figure 5 shows the box plot of monthly precipitation averaged at regional scale for both
16 EXPRESS-Hydro and observations. For each month we have two time series, observed and
17 modeled, of rainfall cumulated values obtained averaging the maps. The comparison
18 highlights that EXPRESS-Hydro reproduces quite well the variability along the 30 years but
19 often underestimates the rainfall amount; this is particularly evident in January, September
20 and October.

21 Figure 6 shows the same analysis of Figure 5 but performed at catchment scale on 4 basins
22 whose characteristics are reported in Table 1; this Figure gives an idea of the performance of
23 EXPRESS hydro at basin scale. It is interesting to evidence that in Entella closed at Panesi
24 and Vara closed at Nasceto, which are located in central-east part of the study region, there is

1 a general underestimation of rainfall during autumnal period, which is not present in the other
2 2 test basins. On the contrary, the box plots on Argentina closed at Merelli and Arroscia
3 closed at Pogli show an overestimation during spring especially on April and May.

4

5 **3.2 Distribution of the annual discharge maxima**

6 In Figures 7 to 9 a series of graphs are presented where a selection of observed and reanalysis
7 driven ADM CDF distributions are compared, together with the GEV obtained by reanalysis
8 driven ADM and the corresponding 95% confidence intervals. For each station both the
9 results obtained with and without rainfall B.C. are reported. The comparisons correspond to
10 six hydrological gauging stations where reliable and long-time series of observed ADM are
11 available.

12 The cases in Figure 7 show a shift of the observed distribution with respect to the modeled
13 one especially without B.C. Low ADM observed values lay out of the confidence intervals of
14 the reanalysis driven ADM GEV distribution, while the most extreme values are inside the
15 confidence intervals. The distributions without bias correction show underestimation of
16 ADM; B.C. leads to very good results for Entella closed at Panesi case and to an
17 overestimation on Bisagno closed at La Presa case.

18 Magra closed at Piccatello (Figure 8) shows an overestimation in both cases, which is getting
19 higher after the B.C; Argentina closed at Merelli benefits of B.C. especially regarding the
20 extreme ADM values.

21 Arroscia closed at Pogli shows an improvement of reanalysis driven ADM, once B.C. is
22 performed, while Nervia ADM without B.C. fits well observations and B.C. leads to an
23 overestimation (Figure 9).

1 The Kolmogorov-Smirnov test with 5% significance level was applied to all the selected
2 stations and corresponding results are summarized in Table 4. It is interesting that BIAS
3 correction does not allow to increase the number of null-hypothesis (data belong to the same
4 distribution) but for both the cases, with and without B.C., we have 9 stations on 15 that pass
5 the test. In some stations B.C. worsens the results while in some other an improvement is
6 observed. Changing the significance level does not change the final findings in a significant
7 way: with 1% 12 stations pass the test with B.C. and 11 without B.C., with 10% 7 stations
8 pass the test with B.C. and 7 without B.C.. This fact could derive on how the B.C., that acts
9 on the monthly volume, affects short and severe rainfall events in different parts of the study
10 area; these intense and short events are often the ones that in many cases cause the ADM.
11 The poor reproduction of ADM in some sections can be due to various causes; on one side it
12 was not possible to calibrate the model all over the study region, on the other side in some
13 periods and in some subregions the rainfall reanalysis is probably poorly representative of
14 actual rainfall and B.C. does not correct it enough. Moreover observed peaks and simulated
15 peaks are often referred to different time periods; this fact, together with the hydro-climatic
16 regime typical of the study region (flash flood regime with high variability of ADM), could
17 have a significant impact on final results.
18 We would like also to highlight the fact that simulated ADM distributions have often similar
19 shapes to the observed ones and suffer of a sort of bias (for example Bisagno closed at La
20 Presa, Figure 7), while in other cases the simulated ADM distribution is only partially out of
21 the confidence intervals (example Argentina closed at Merelli, Figure 8). The average
22 hydrologic regime on the study region could be only partially affected by the local bad
23 fittings, and this is confirmed by the analysis of the regional growing curve in section 3.3.

1 3.3 Regional analysis of the annual discharge maxima

2 Figure 10 shows the comparison between the non dimensional regional growth curve obtained
3 fitting a GEV on simulated ADM obtained with and without B.C., the observations (available
4 ADM on Liguria Region) and the Simulated ADM; results are quite good even if it seems that
5 modeling chain without B.C. leads to a small underestimation of high frequency events (low
6 T) and a small overestimation of low frequency events (high T) in respect to the observations.
7 Anyway both observed and modeled ADM lay inside the confidence intervals (95 %) for a
8 large part of the curve.

9 In the Figure we reported the curves built using simulations of all the sections with drainage
10 area larger than A_{th} together with those obtained using only the sections where the
11 hydrological model was calibrated. The curves that used only calibrated sections are really
12 similar to those built using all the sections, this proves that this latter option enhances the
13 robustness of the regional curve estimation without introducing evident errors.

14 The main differences in the case of B.C. configuration are that observations lay always inside
15 the confidence intervals and there is a better matching between simulated and observed
16 sample curves. This is a significant finding in fact the regional curve is an important
17 ingredient to deal with quantile estimation in ungauged sections.

18 To compare the quantiles estimated using the modelling chain with those obtained in Boni et
19 al. (2007) the following ratio was considered:

$$20 \quad Ratio(T) = \frac{Q(T)_{Model}}{Q(T)_{Reg}} \quad (8)$$

21 where Model and Reg stand for modelling chain and regional analysis, T is the return period,
22 Q is the ADM. Ideally, if modelling chain provided exactly the same results of the benchmark
23 regional analysis, the Ratio(T) value should be around 1; Ratio(T) > 1 means overestimation
24 in respect to the benchmark, Ratio(T)<1 means underestimation.

1 Figure 11 shows Ratio(T) for T=2.9 years (Index Flow) as function of the drainage area (A in
2 km²), while Figure 12 shows the maps of Ratio(T) for T=2.9 years and T=50 years.

3 The first consideration is that it appears to exist a relation between Ratio(T) and A, probably
4 the chain cannot reproduce in detail meteorological and hydrologic processes at very small
5 time and spatial scales, that produces sufficient runoff for extreme flow estimation (Siccardi
6 et al., 2005). In fact for A < 30-50 km² the underestimation seems quite systematic even if
7 B.C. improves results. Ratio(T) shows a general underestimation also for A>30-50 km² but
8 B.C. generally leads to a better distribution between over- and underestimation. From Figure
9 12 is noticeable that there is a general improvement driven by B.C. especially in those areas
10 where the model chain without B.C. underestimates Q(T). Ratio(T) for T= 50 years and T=2.9
11 years (Figure 12) have a similar pattern.

12 In the centre of Liguria Region the Ratio(T) obtained by using EXPRESS-Hydro leads to
13 results which are comparable with findings of Boni et al. (2007) even without B.C., while
14 simulations with B.C. apparently seem affected by overestimation. This could be due to
15 different causes: i) it is possible that EXPRESS-Hydro well reproduces the events at small
16 time and spatial scales (3-6 hours, 10-100 km²) in that part of the region but generally
17 underestimates monthly cumulates, in this case B.C. could lead to streamflow overestimation;
18 ii) hydrological model could need a better calibration, but this is in our opinion not the case
19 since in a calibrated basin B.C. leads to overestimation even in the site comparison (Bisagno
20 creek, section 3.2) iii) we could also consider the possibility that maybe Boni et al. (2007)
21 underestimates quantiles in this area. It has to be noticed that overestimation for T=2.9 years
22 is larger than that for T=50 years, this is probably due by the fact that the shape of the
23 growing curve in the B.C. case leads to a reduction of the overestimation when T increases;
24 western part of Liguria has similar behaviour even if less stressed and mainly evident for
25 larger basins only.

1 The underestimation on smaller catchments ($A < 30\text{-}50 \text{ km}^2$) could be partially due by a not
2 optimal parameterization of hydrological model (especially where calibration was not
3 possible), but it appears more reasonable that the errors related to parameterization would lead
4 to a uniform-like distribution between over and underestimation. However, the model spatial
5 resolution could play a role since the representativeness of catchment morphology degrades
6 for small drainage areas with a general smoothing effect that affects results; it is true that we
7 put a threshold for the analysis (basins with $\text{Area} < 16 \text{ km}^2$ are neglected) but the degradation
8 effect is clearly continuous from large to small drainage areas.

9 A further cause is presumably the fact that EXPRESS-Hydro cannot always adequately
10 reproduce the rainfall structures at fine spatial and temporal scale, and the downscaling
11 procedure can only partially correct this lack. Moreover the employed time resolution (1 hour
12 after downscaling) could be not sufficient in some cases when drainage area is small
13 (Silvestro et al., 2016; Reborá et al., 2013); as a consequence, the runoff processes needed to
14 trigger such very small catchments in these cases are not properly modelled (Siccardi et al.,
15 2005).

16 The combination of the aforementioned factors leads us to consider that the underestimation
17 of quantiles for very small catchments (i.e. $A < 30\text{-}50 \text{ km}^2$) is a structural problem of the
18 modelling chain.

19 This fact is corroborated by the analysis shown in Figure 13, left panel. The $\text{Ratio}(T)$
20 averaged on the target area is plotted as a function of T for all the sections with drainage Area
21 $\geq 16 \text{ km}^2$. Ratio increases with T especially for the B. C. case, this means that growth curve
22 values ($K(T)$) obtained by EXPRESS-Hydro partially balance the underestimation of average
23 ADM (used as Index Flow) in the estimation of higher quantiles. $\text{Ratio}(T=2.9 \text{ years})$ changes
24 from 0.47 to 0.71, $\text{Ratio}(T=50 \text{ years})$ changes from 0.45 to 0.66. If we increase the threshold

1 area from 16 to 50 km² (Figure 13, right panel) results improve with a reduction of the
2 underestimation for both cases (with and without B.C.).
3 As already shown the general underestimation of Ratio(T) for small catchments is not
4 completely confirmed for all the region, in the central part of Liguria Region there is an area
5 where results are quite good even for basins with Area < 50 km²; bias correction leads to an
6 overestimation of Ratio(T) in some cases. Apparently in this area EXPRESS-Hydro can
7 produce rainfall spatial-temporal structures able to trigger flood events compatible with the
8 hydro-climatology of small basins. This is also the area of the study region that previous
9 studies demonstrated to be characterized by highest values of rainfall maxima for 1, 3, 6, 12
10 and hours (Boni et al., 2008).

11 **3.4 Effects of the rainfall downscaling on simulated ADM**

12 In order to assess the influence of the rainfall downscaling, the modelling cascade was applied
13 without using the rainfall downscaling. In this way for each pixel of the domain a 30 years
14 length time series of ADM was obtained by the hydrological model driven with the bias
15 corrected rainfall reanalysis which has not a spatial and temporal pattern below the native
16 EXPRESS-Hydro resolution. The rainfall field was considered with constant intensity over 3
17 hours and simply gridded from 4 km to 1 km.

18 We computed the average ADM over 30 years and we compared it with the one obtained by
19 the complete chain on each pixel by estimating the following ratio:

$$20 \quad RatioDS = \frac{Q_{MeanNoDS}}{Q_{MeanDS}} \quad (9)$$

21 The RatioDS was then plot versus the drainage area obtaining the graph in Figure 14.

22 It is evident how the downscaling affects the results, the impact generally increases when
23 drainage area decreases, it is crucial to simulate the ADM on small catchment when drainage

1 area is lower than 100-150 km². The analysis evidences how the underestimation of quantiles
2 shown in section 3.3 would be enhanced without using the rainfall downscaling procedure.

3 **3.5 Water balance and runoff ratio**

4 In this section some considerations about the long-term water balance are shown in order to
5 evaluate how the applied system can reproduce hydrological cycle and some variables
6 interesting for water balance and water management purposes.

7 Since among the model' output there are maps of evapotranspiration, we estimated the
8 distributed runoff ratio (RR) at cell scale as:

$$9 \quad RR(x, y) = \frac{Rain(x,y) - Evt(x,y)}{Rain(x,y)} \quad (10)$$

10 Where Rain(x,y) and Evt(x,y) are the total modeled rainfall and evapotranspiration in the cell
11 which has coordinates (x,y) over the 30 years of simulation: this is interesting to have an idea
12 of the pattern of RR over the region. The maps of RR are shown in Figure 15, together with
13 maps of annual mean rainfall for both cases: with and without B.C..

14 Spatial pattern of RR is strongly correlated to spatial pattern of precipitation, and this latter is
15 evidently related with orography especially for the case without B.C..

16 When a single cell has a large number of upstream cells, it tends to be frequently saturated
17 because of the contributions of subsurface flow of the upstream cells. As a consequence we
18 decided to not show the values in the cells that belong channel network as modeled by the
19 hydrological model (Giannoni et al., 2005), because they are poorly representative (generally
20 the values are very low and even negative).

21 B.C. produces an increasing of precipitation all over the entire region and a reduction of
22 differences between coastal and inland areas. Even the runoff ratio increases with rainfall
23 B.C.

1 In order to estimate how the modeling chain reproduces the available observations we
2 calculated the runoff ratio at basin scale on a target section s with:

$$3 \quad RRs(s) = \frac{VQ(s)}{Rain(s)} \quad (11)$$

4 where $Rain(s)$ is the accumulated rainfall over the basin upstream the section s and $VQ(s)$ is
5 the integral on time of streamflow volume passed through section s . We considered some
6 closure sections where runoff ratio estimated by observations (rainfall and streamflow) is
7 available (see Table 1). They can be found in the Hydrologic Annual Survey
8 (<http://www.arpal.gov.it/homepage/meteo/pubblicazioni/annali-idrologici.html>), which is an
9 official document published by the Regional Agency for Environment Protection. The
10 observed runoff ratios are not available for the simulation period (1979-2008) but they are
11 estimated as an average of values available on non-continuous periods since about 1940 to
12 nowadays, thus they are a possible benchmark to assess the performance of the modeling
13 chain.

14 Results are reported in table 5. Modeled RRs are compatible with the hydro-climatology of
15 the target area (Barazzuoli and Rigati, 2004; Provincia di Imperia, 2017) but at the same time
16 it is evident a general underestimation in the western part of the region (basins 4,5,6). B.C.
17 improves results and RRs are more similar to the benchmark.

18 The rainfall B.C. introduces only small variations in terms of runoff ratio, this means that
19 considering the long term water balance, the increasing or decreasing of rainfall lead on
20 similar percentage variation on both runoff and evapotranspiration.

21 For example, in the center and eastern parts of Liguria, B.C. leads to a general increasing of
22 precipitation and to a reduction of the orographic features of the spatial pattern, but at the
23 same time the evapotranspiration increases, consequently RRs have a small increase
24 considering B.C. case. As shown in sections 3.2 and 3.3 the increasing of rainfall leads to
25 larger values of ADM, but the RRs do not change significantly.

1 This result could be due to the fact that even other EXPRESS-Hydro variables would need
2 correction, we refer for example to the solar radiation or to wind speed which are important
3 forcings for energy balance (and so for long term water balance), but no reliable and dense
4 data are available for the entire simulation period. Another reason could be found in the
5 hydrological model, since a calibration more devoted to preserve long term runoff could lead
6 to better results. In any case we could say that generally the results are good and they
7 highlight the potentialities of using such modeling chain even for water balance purposes.

8 **4 Discussion and conclusions**

9 This work explores the possibility of using EXPRESS-Hydro, a high-resolution regional
10 dynamical downscaling of ERA-Interim reanalysis meteorological dataset with the state-of-
11 the-art non-hydrostatic Weather Research and Forecasting (WRF) regional climate model, for
12 hydrological purposes on small catchments. This was done using a subset of EXPRESS-
13 Hydro meteorological variables as input to a distributed continuous hydrological model to
14 produce streamflow simulations. The rainfall fields were downscaled from the original
15 spatial-time resolution (4km, 3 hours) to a finer one (1km, 1 hours). All the analysis was
16 conducted with and without applying a bias correction to rainfall fields. The study area is the
17 Liguria Region in Italy with a particular focus on Tyrrhenian coast.

18 Firstly we evaluated the performance of the presented modelling chain in reproducing
19 extreme streamflow statistics. This was done following two approaches: i) comparing
20 statistical distribution of ADM with observations in some measurement points ii) using as
21 benchmark the regional analysis presented in Boni et al. (2007) that allows a comparison with
22 a distributed perspective.

23 Secondly we evaluated how the modeling chain reproduces the long term water balance
24 analyzing the modeled runoff ratios and using estimations based on observations as
25 benchmark.

1 The results are encouraging even if the modelling chain cannot always reproduce with high
2 accuracy the considered benchmarks. The ADM statistic is reproduced quite well in various
3 parts of the target region but there are sub-regions where there is alternatively a general
4 underestimation or overestimation of the quantiles. Rainfall B.C. leads to a general
5 improvement reducing the underestimation but introducing an overestimation in some basins
6 especially in the central part of the region.

7 Comparison of modelled and observed ADM on single sites shows that for a large number of
8 the measurement sites the time series belong to the same distribution with significance 5%;
9 the fitting of modelled ADM with GEV distributions are generally good and often the
10 observations lay inside the confidence intervals at 95% of significance, especially for low
11 frequent quantiles. Anyway B.C. sometimes worsen the results, there are sites where the GEV
12 fitting without B.C. is better than that with B.C.

13 Comparison with regional analysis shows interesting results with different behaviour in
14 different parts of the region depending on how EXPRESS-Hydro generates the spatial-
15 temporal patterns of precipitation and how rainfall bias correction corrects the quantitative
16 amounts.

17 Both punctual and distributed analysis show that there is a general underestimation for basins
18 with drainage area smaller than 30-50 km² but B.C. considerably corrects this
19 underestimation. This is probably due to structural problems of the modelling chain under the
20 aforementioned drainage area; for this class of basins it is necessary to further go down with
21 time and spatial scales in generating meteorological input, especially precipitation (Siccardi et
22 al., 2006; Silvestro et al., 2016), and presumably even in hydrological modelling (Yang et al.,
23 2001). A possibility to deal with very small basins is study a way to better exploit the
24 potentialities of the downscaling algorithm (RainFARM), that is here used in a deterministic
25 way only to generate a possible temporal-spatial pattern with 1h and 1 km spatial resolution

1 but maintaining the precipitation volumes and structures generated by EXPRESS-Hydro at its
2 native resolution (3 hours, 4 km).
3 Runoff ratio RR was used as indicator to evaluate long term water balance. The RR
4 coefficient evaluated on 30 years length simulation period at cell scale, has reasonable values
5 for the climatology of the region (Barazzuoli and Rigati, 2004; Provincia di Imperia 2017)
6 and its pattern is highly correlated with annual mean rainfall pattern. RR at basin scale was
7 compared with estimations based on observations for some measurement points, the values
8 are quite good as order of magnitude but generally the modelling chain underestimates in both
9 analyzed configurations even if B.C. improves the results. This could be due to the fact that
10 also the variables related to energy balance (for example the solar radiation and wind)
11 modelled by EXPRESS-Hydro probably need correction, this opportunity is not developed in
12 the presented work, mainly for lack of reliable and sufficiently dense data.

13 To summarize the results of the presented investigation, we could state that the perspective of
14 using the present modelling chain to produce hydro-meteorological statistical analysis in the
15 study area is good, even if some difficulties and lacks were emphasized by the study. The
16 fully distributed approach allows to reproduce the hydro-climatic characteristics and features
17 in a continuous way along the territory. Rainfall B.C. contributes in a relevant way to improve
18 the results, helping the system to better model some rainfall characteristics not completely
19 captured even by a high-resolution meteorological reanalysis. Very small basins (Area < 30-
20 50 km²) generally suffer of a structural underestimation partially corrected by B.C..

21

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2 **5 Tables**

Basin	Section	ADM 30 years time series	Hourly discharge data	Runoff ratio	Area [km ²]	Mean Slope [%]	Mean height [m]
Magra	Calamazza	X	X		1650	18	503
Magra	Piccatello	X		X	78	21	590
Vara	Nasceto	X	X	X	202	23	651
Petronio	Riva Trigoso	X			55	19	401
Graveglia	Caminata	X			43	24	590
Entella	Panesi	X	X	X	364	21	535
Lavagna	San Martino	X			163	23	570
Bisagno	Passerella Firpo		X		92	20	398
Bisagno	La Presa	X			34	25	520
Sansobbia	Ponte Poggi	X			33	21	470
Neva	Cisano	X	X	X	123	25	670
Arroscia	Pogli	X	X	X	204	27	650
Impero	Rugge	X			73	19	480
Argentina	Merelli	X	X	X	188	26	883
Nervia	Isolabona	X			123	22	690
Tanaro	Ponte Nava	X			147	23	1350

Bormida	Murialdo		X		134	19	820
Bormida	Piana Crixia		X		273	15	550
Orba	Tiglieto		X		76	21	560
Aveto	Cabanne		X		33	23	1130

1 Table 1: availability of discharge data used for model validation, ADM analysis, long term
2 mass balance analysis. The characteristics of the basins upstream each measurement station
3 are reported.

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Basin	Section	u_c [$m^{0.5}s^{-1}$]	u_h [s^{-1}]	c_t [-]	c_f [-]	NS	REHF
Magra	Calamazza	127	0.0001 94	0.3	0.05	0.81	0.14
Vara	Nasceto	125	0.0001 91	0.5	0.035	0.83	0.10
Entella	Panesi	64	0.0001 92	0.3	0.05	0.77	0.18
Bisagno	Passerella Firpo	110	0.0005 56	0.5	0.05	0.26	0.16
Neva	Cisano	63	0.0001 94	0.3	0.05	0.71	0.25
Arroscia	Pogli	65	0.0001 92	0.3	0.02	0.74	0.31
Argentina	Merelli	62	0.0001 85	0.3	0.035	0.84	0.21
Bormida	Murialdo	85	0.0001 74	0.3	0.05	0.35	0.51
Bormida	Piana Crixia	66	0.0002 00	0.5	0.02	0.76	0.41
Orba	Tiglieto	114	0.0002 78	0.5	0.02	0.88	0.21
Aveto	Cabanne	69	0.0005 20	0.5	0.02	0.73	0.41

2 Table 2: hydrological model validation; skill score values obtained for the calibrated. The
3 calibrated parameters are also reported. V_{wmax} [mm] and R_f [-] have values 500 mm and 1 for
4 all the basins.

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	BIAS [mm]	RMSE [mm]
DJF	-10.47	60.21
MAM	-0.71	56.13
JJA	-47.71	59.58
SON	-89.55	120.73

2 Table 3: Comparison between observations and EXPRESS-Hydro. Skill scores estimated on
3 seasonal time scale.

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Basin	Section	P value	K-S test	P value (B.C.)	K-S test (B.C.)
Magra	Calamazza	0.008	NO	0.855	Yes
Magra	Piccatello	0.036	NO	0.021	NO
Vara	Nasceto	0.632	Yes	0.012	NO
Petronio	Riva Trigoso	0.780	Yes	0.023	NO
Graveglia	Caminata	0.030	NO	0.065	Yes
Entella	Panesi	0.002	NO	0.990	Yes
Lavagna	San Martino	0.062	Yes	0.701	Yes
Bisagno	La Presa	0.056	Yes	0.022	NO
Sansobbia	Ponte Poggi	0.350	Yes	0.005	NO
Neva	Cisano	0.420	Yes	0.110	Yes
Arroscia	Pogli	0.172	Yes	0.820	Yes
Impero	Rugge	0.003	NO	0.860	Yes
Argentina	Merelli	0.078	Yes	0.218	Yes
Nervia	Isolabona	0.206	Yes	0.449	Yes
Tanaro	Ponte Nava	0.001	NO	0.034	NO

5 Table 4: Kolmogorov-Smirnov test with 5% significance. P values are reported together with
6 verification of null-hypothesis (data belong or not to the same distribution).

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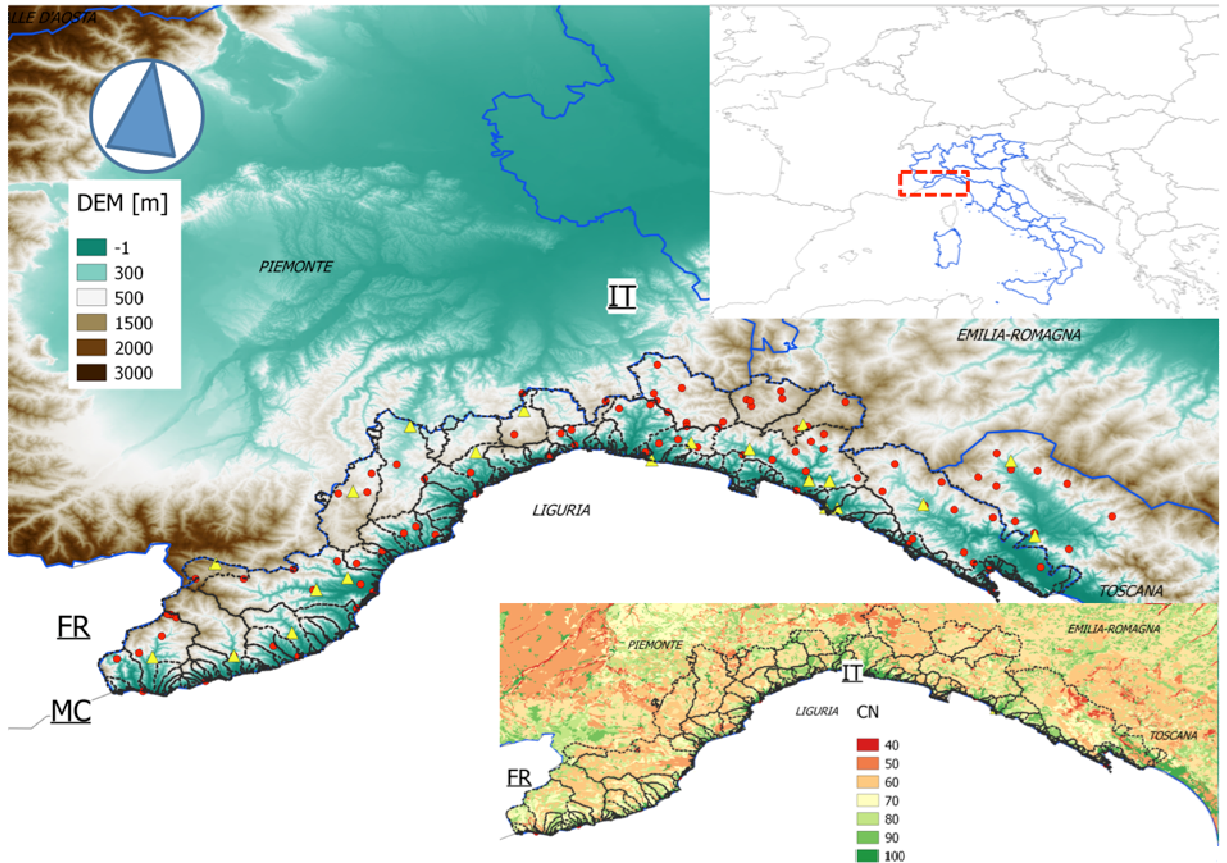
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Basin	Section	N. Progr	Area [km ²]	Obs. RR.	Model RR	Model RR (B.C.)
Magra	Piccatello	1	78	0.61	0.62	0.63
Vara	Nasceto	2	202	0.7	0.64	0.66
Entella	Panesi	3	364	0.73	0.64	0.67
Neva	Cisano	4	123	0.59	0.47	0.49
Arroscia	Pogli	5	204	0.55	0.48	0.51
Argentina	Merelli	6	188	0.65	0.51	0.53

4 Table 5. Runoff ratios (RR) obtained by the modeling chain (with and without the
5 rainfall bias correction) compared to those estimated by observations.

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1 6 Figures



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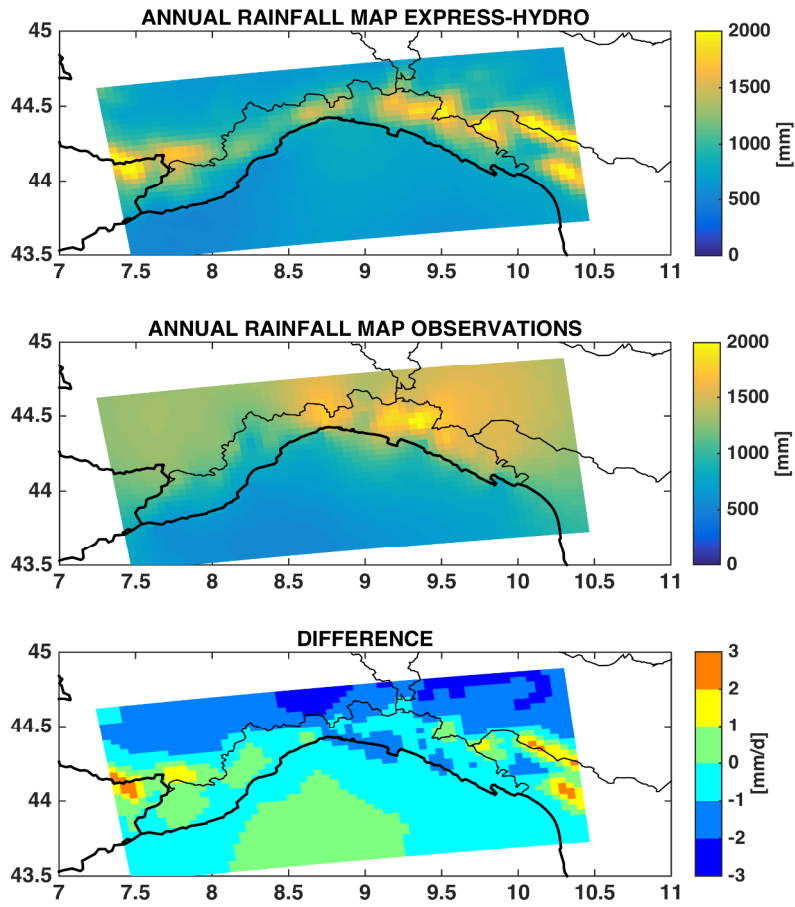
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Figure 1. Study area. Blue lines represent the regional boundaries of Italy, dashed line shows the main catchments of the study region, red dots represent the meteorological rain-gauge station of Liguria region of Italy where 32 years (1978-2010) of daily data are available, yellow triangles are the level gauge sections. Digital elevation model highlights the morphology of the region. In the bottom right corner the curve number map is reported to show synthetically the usage of soil.

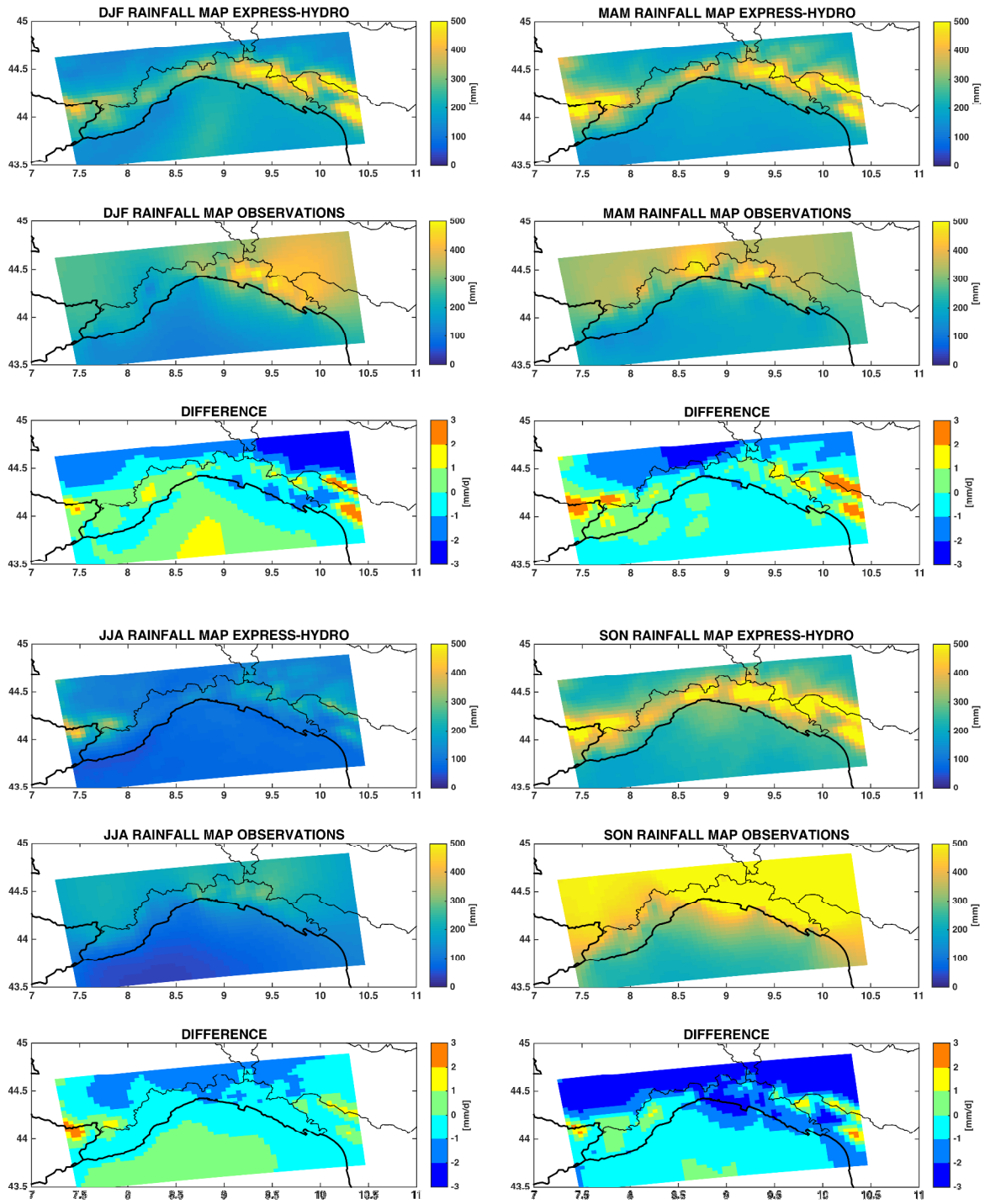
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Figure 2. Upper panel shows the average annual rainfall map over Liguria area, the middle panel shows the average observed annual rainfall map, while the bottom one shows their difference in mm/d.

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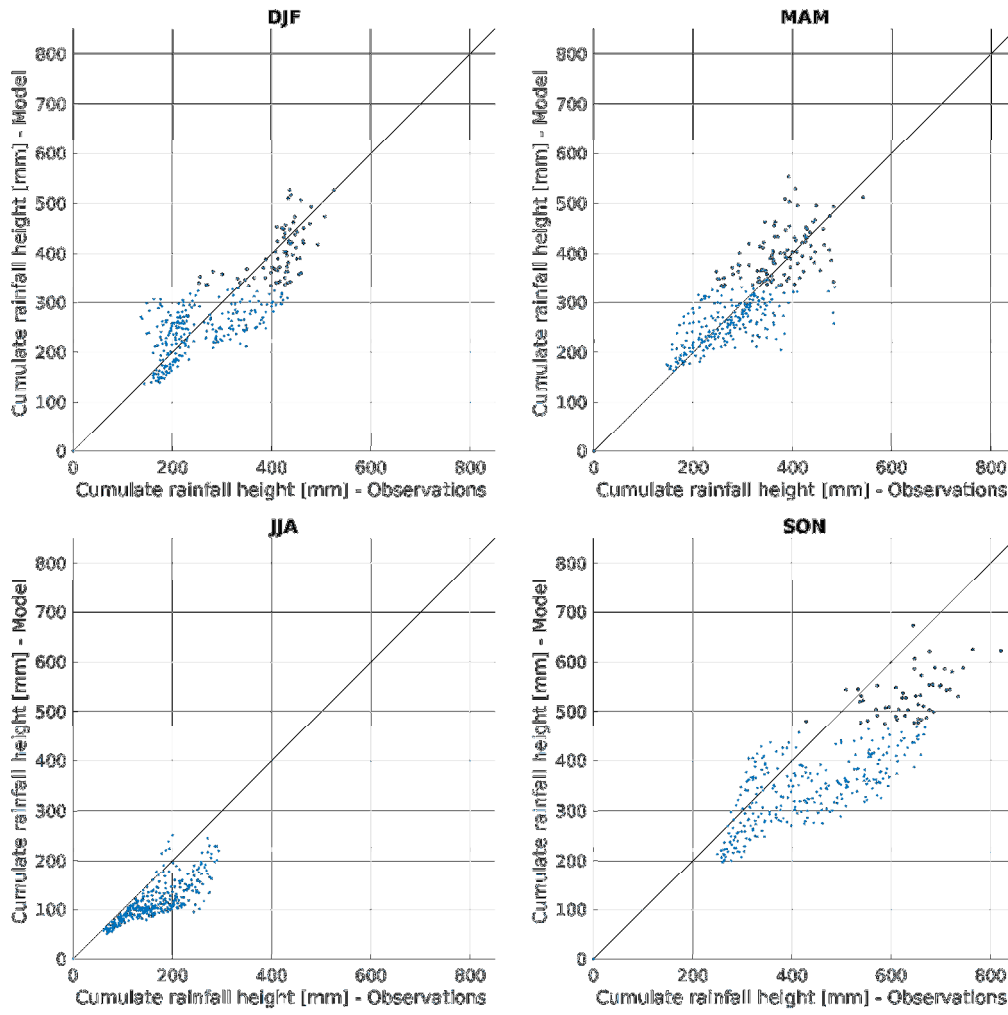
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3 Figure 3. Upper panel shows the average DJF, MAM, JJA, SON rainfall maps over Liguria.

4 For each season 3 maps are shown: EXPRESS-Hydro rainfall map, observed rainfall map,
5 difference map in mm/d.

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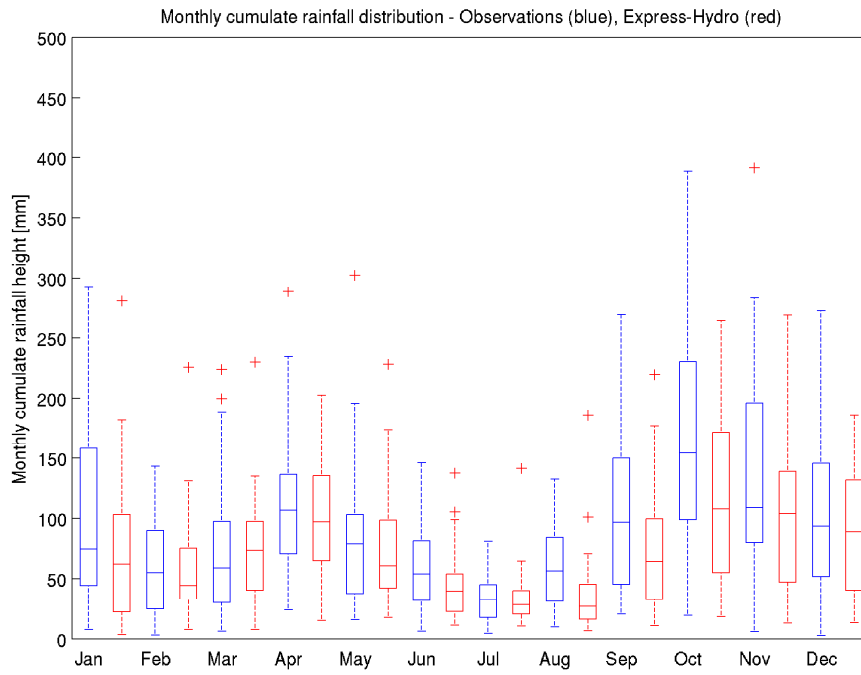
3 Figure 4: Scatter plots of seasonal precipitation built used data on EXPRESS-Hydro spatial
4 resolution (pixel to pixel comparison). X axis reports observed interpolated rainfall, Y axis
5 reports EXPRESS-Hydro estimation.

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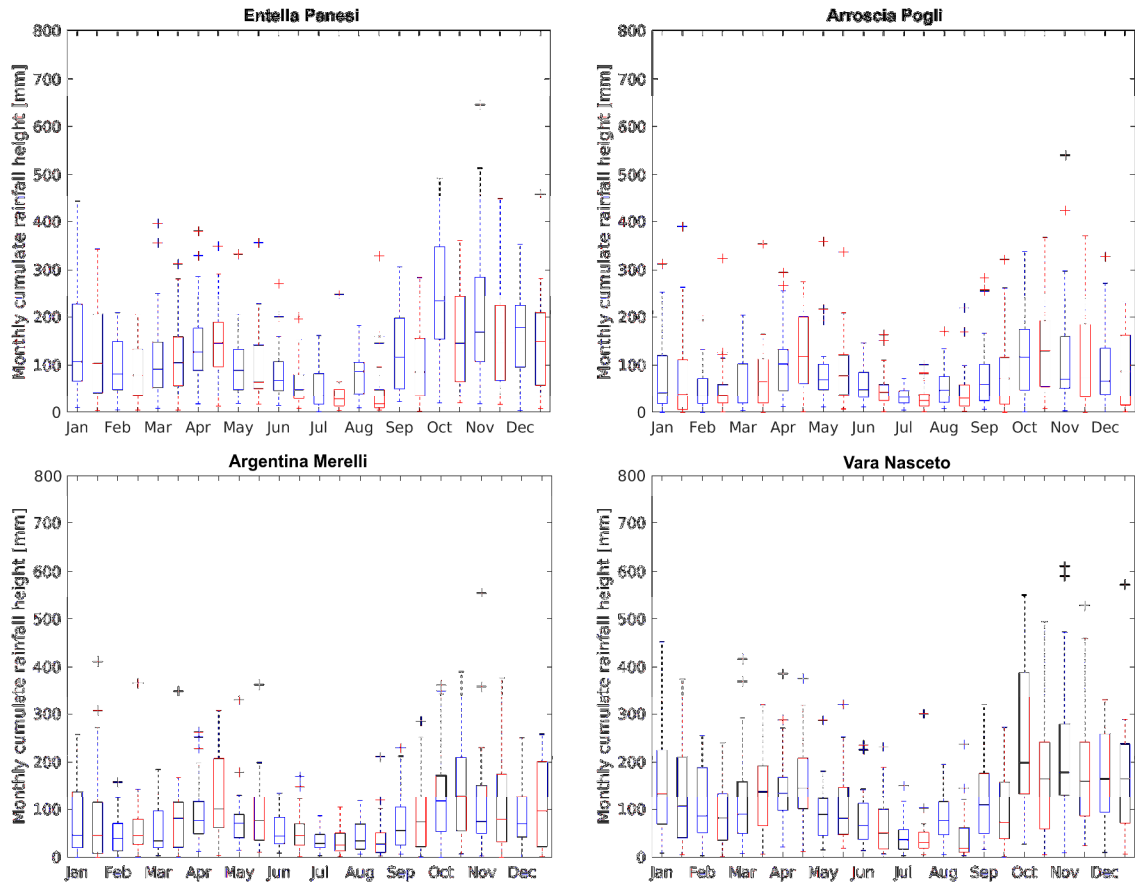


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3 Figure 5: Box plot of monthly precipitation averaged at regional scale. Blue box plots are
4 built with observations while red ones with EXPRESS-Hydro reanalysis.

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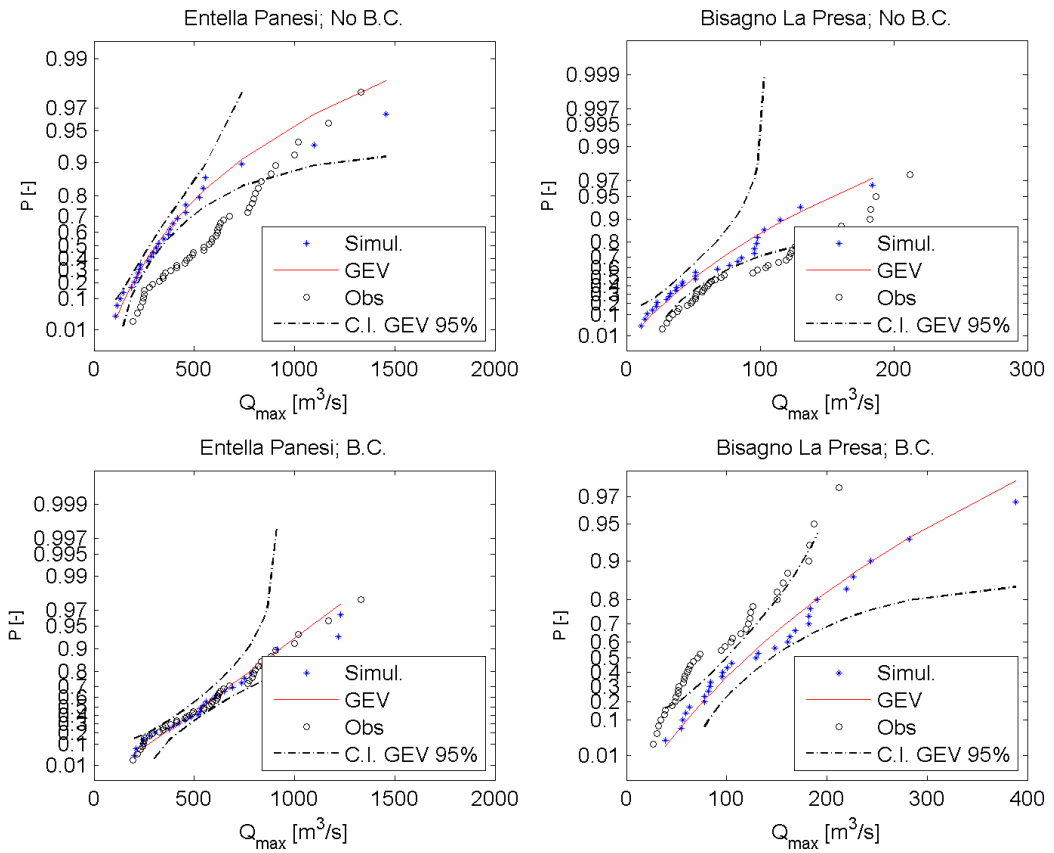
3 Figure 6: Box plot of monthly precipitation averaged at basin scale for 4 test catchments. Blue
4 box plots are built with observations while red ones with EXPRESS-Hydro reanalysis.

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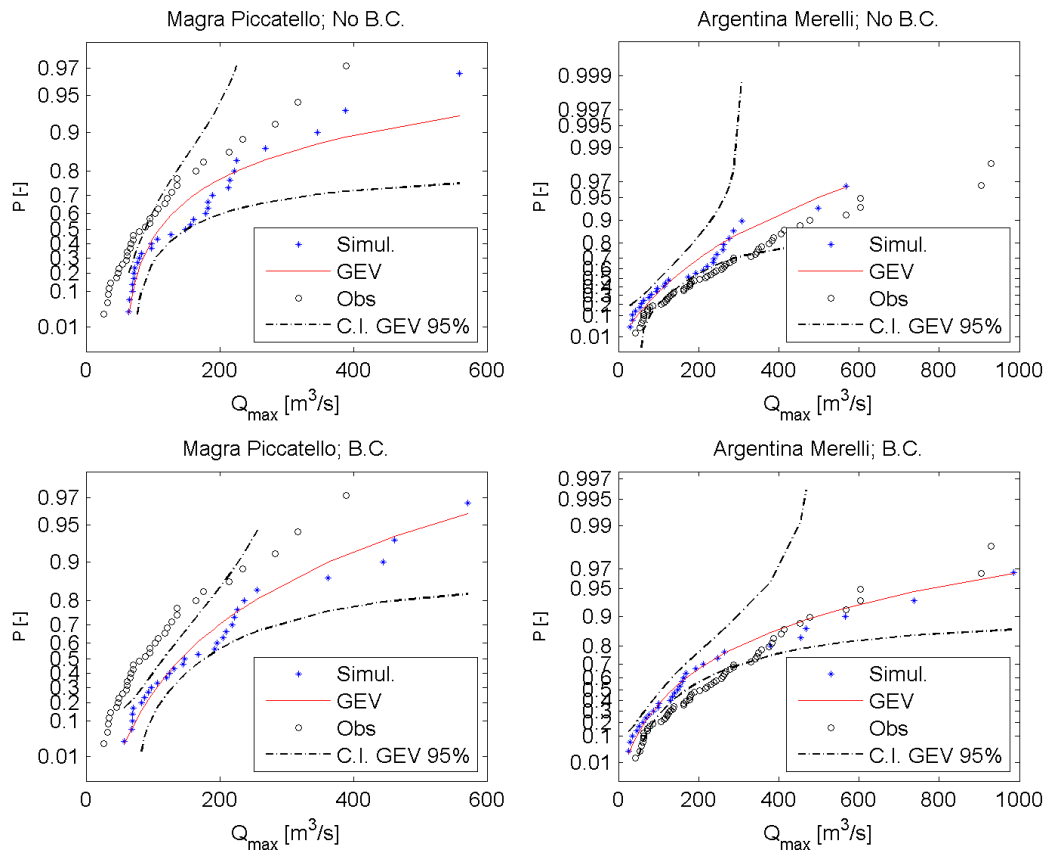


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5 Figure 7. Distribution of ADM for Entella closed at Panesi (364 km²) and Bisagno
6 closed at La Presa (34 km²). Blue dots are the simulated ADM, black dots are observed
7 ADM, red line is the GEV fitted on simulated ADM while dotted lines are confidence
8 intervals with 95% significance. Upper panels show results without rainfall bias
9 correction, bottom panels show results with rainfall bias correction.

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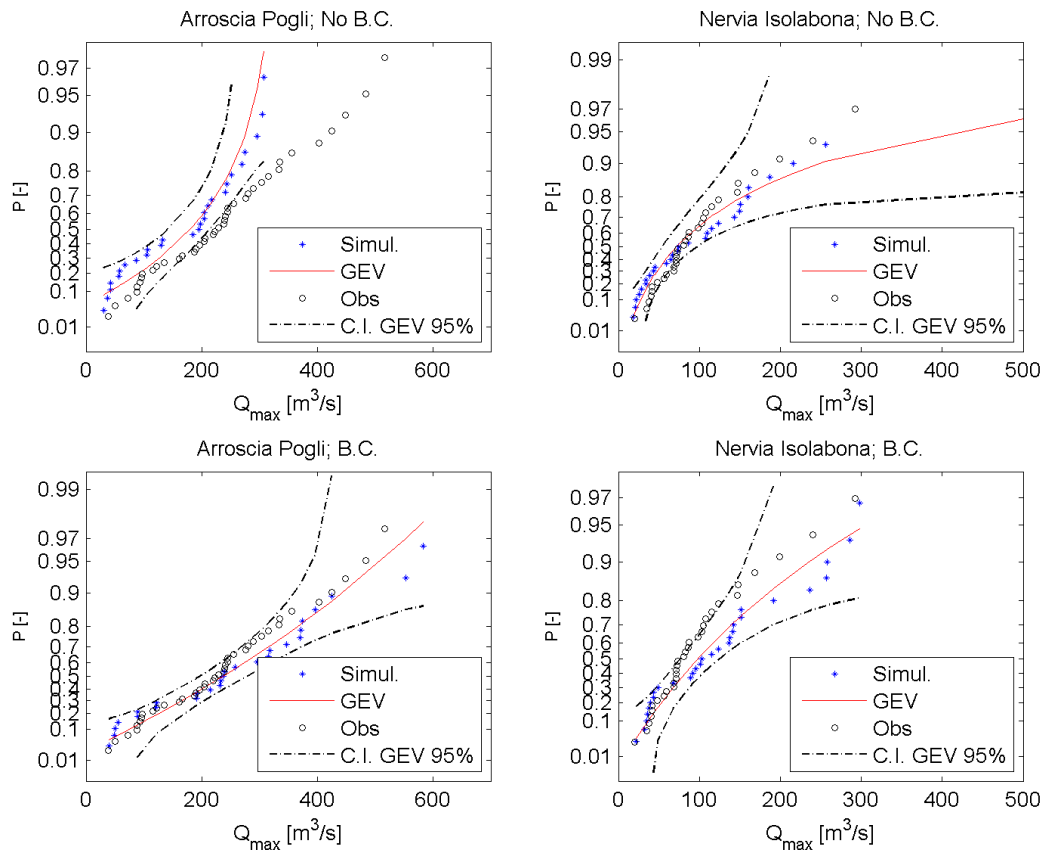
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Figure 8. Same as figure 6 but for Magra closed at Piccatello (78 km^2) and Argentina

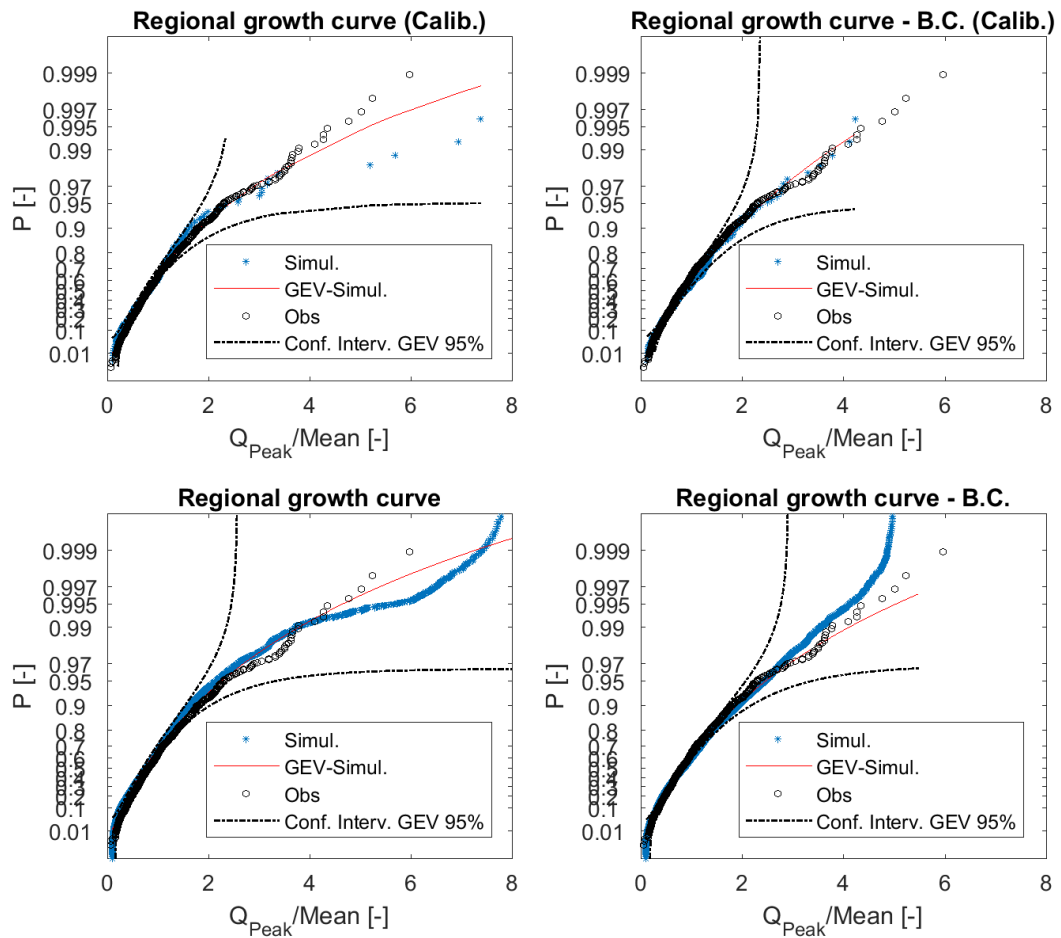
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closed at Merelli (188 km^2).



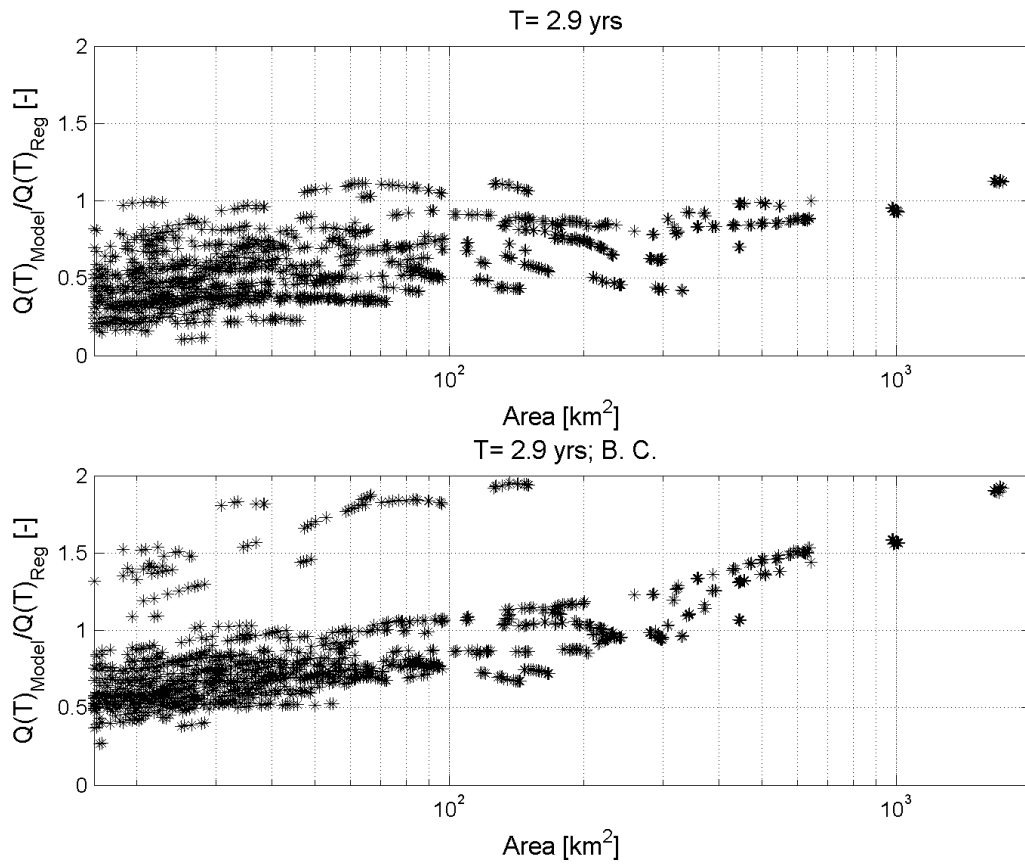
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Figure 9: Same as figure 6 but for Neva closed at Cisano (123 km²) and Nervia closed at Isolabona (122 km²).



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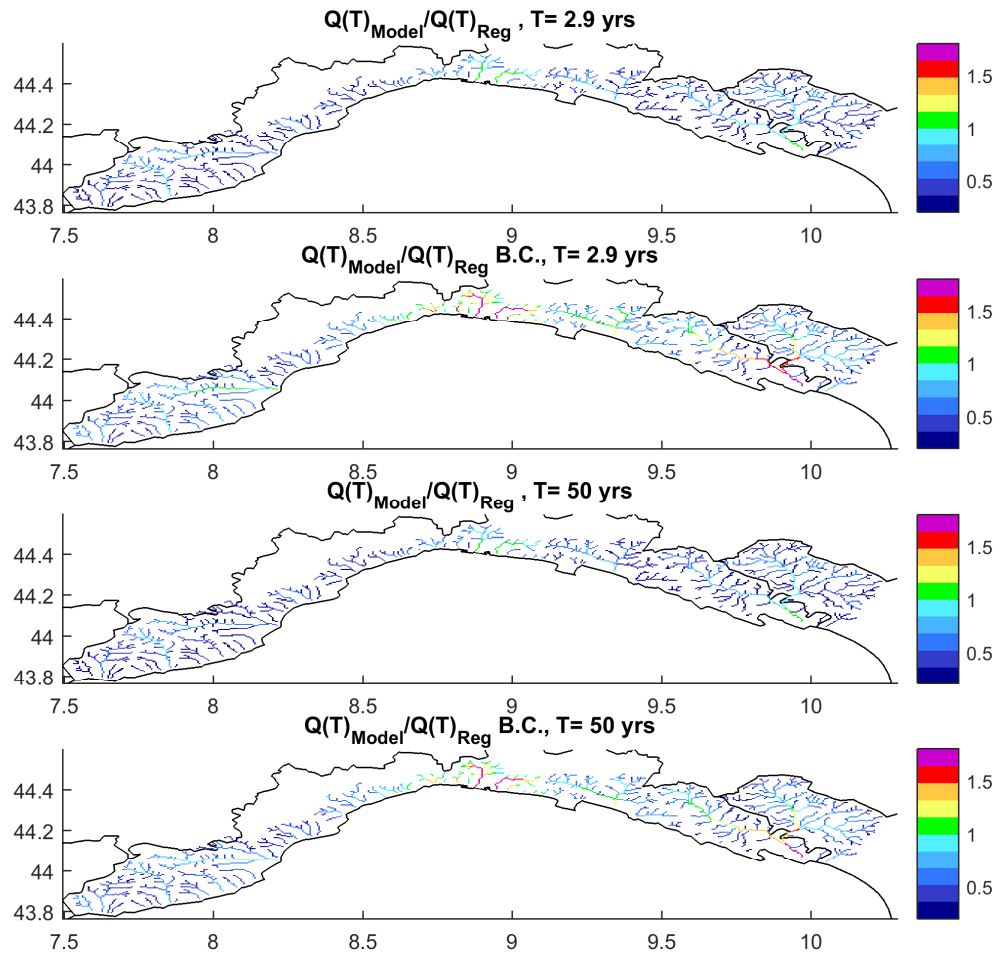
Figure 10. Sample growth curve obtained by model chain (blue dots) compared with observations (black dots). Red line is the GEV distribution fitted on modeled values while dotted lines are the confidence intervals with significance 95%. Top panels: results without and with rainfall bias correction using the sections where hydrological model was calibrated. Bottom panels: results without and with rainfall bias correction using all the closure section with drainage area larger than A_{th} .



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Figure 11. Ratio(T) as a function of drainage area. T=2.9 years which correspond to index flow. Upper panel shows results without rainfall bias correction, lower panel (B.C.) with rainfall bias correction.

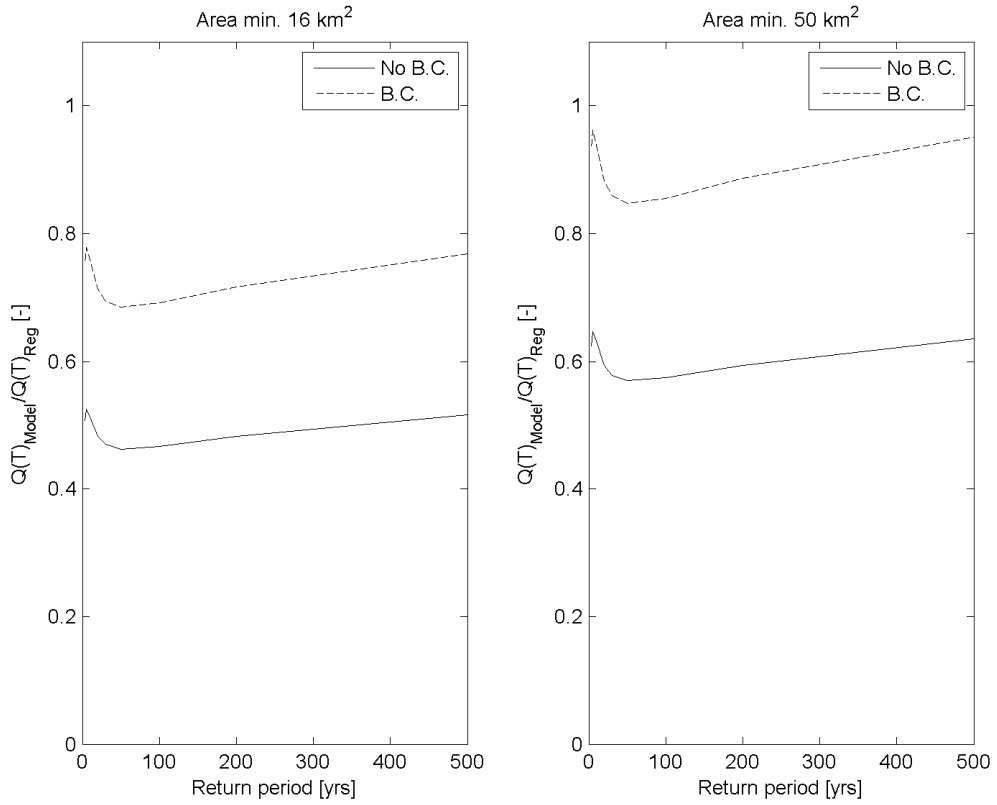
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Figure 12. Maps of Ratio(T) for T=2.9 and 50 years. Upper panel shows results without rainfall bias correction, lower panel (B.C.) with rainfall bias correction. The B.C. increases the percentage of drainage network points that have values around 1.

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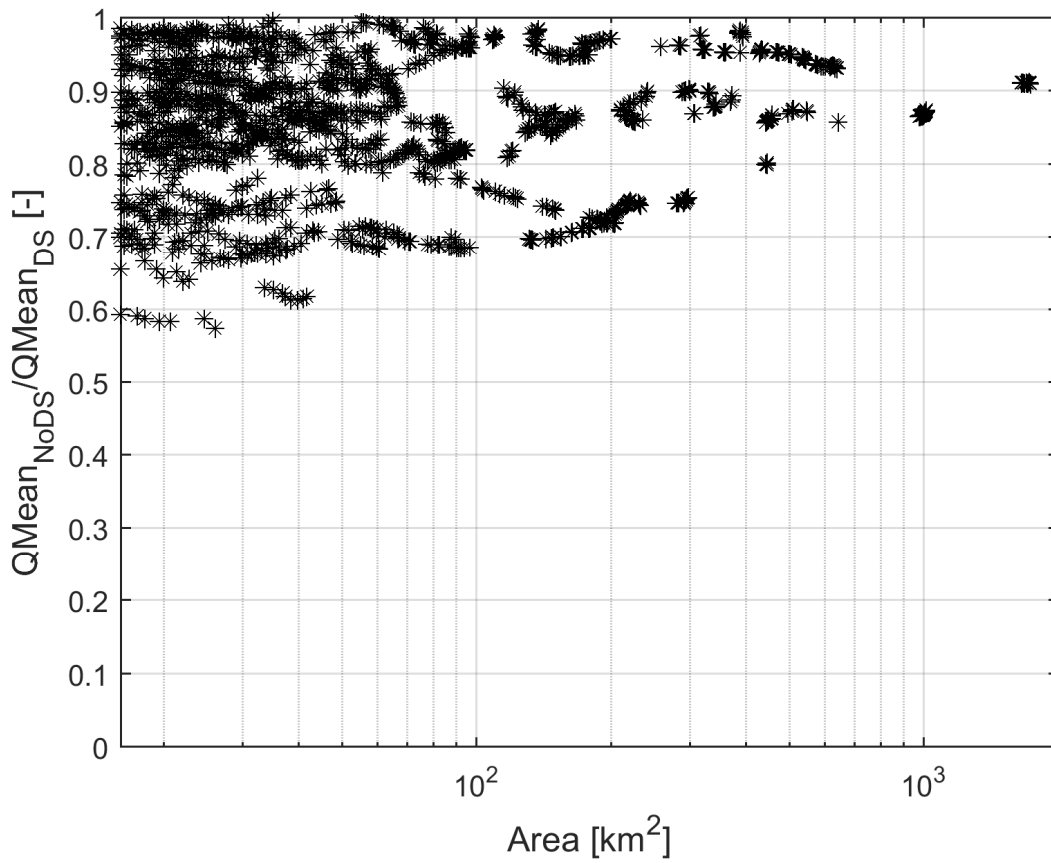


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3 Figure 13. Mean Ratio(T) over the considered domain as a function of T. Continuous line (no
4 B.C.) is the case without rainfall bias correction, dotted line (B.C.) is the case with rainfall
5 bias correction. Left panel is the case where points with drainage area lower than 16 km² are
6 discarded; right panel is the case where points with drainage area lower than 50 km² are
7 discarded.

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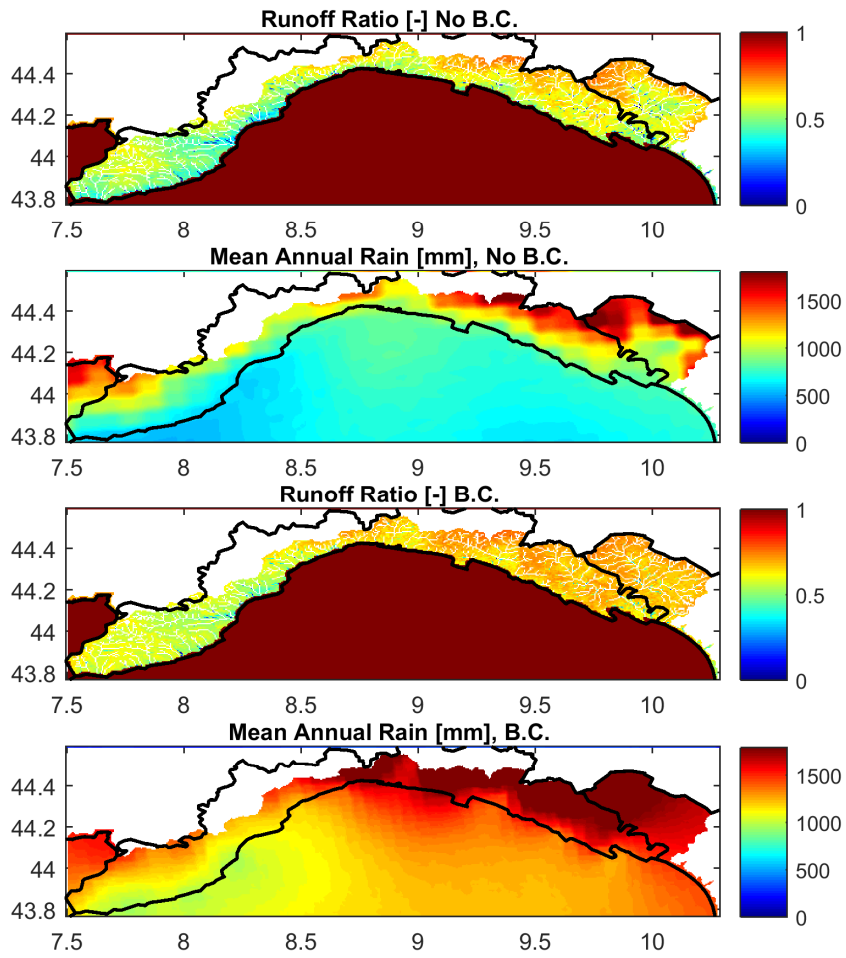
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3 Figure 14. Ratio between mean flow estimated without and with downscaling as a function of
4 drainage Area. The graph shows that the impact of rainfall downscaling increases when basin
5 drainage area decreases.

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Figure 15. Distributed runoff ratio and mean annual rainfall. Upper panels show the model estimation without B.C. while lower panels with B.C. .