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Producing hydrologic scenarios from raw climate model outputs using an asynchronous modelling framework

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Abstract. Statistical post-processing of climate model outputs is a common hydroclimatic modelling practice aiming to produce climate scenarios that better fit in-situ observations and to produce reliable stream flows forcing calibrated hydrologic models. Such practice is however criticized for disrupting the physical consistency between simulated climate variables and affecting the trends in climate change signals imbedded within raw climate simulations. It also requires abundant good-quality meteorological observations, which are not available for many regions in the world. A simplified hydroclimatic modelling workflow is proposed to quantify the impact of climate change on water discharge without resorting to meteorological observations, nor for statistical post-processing of climate model outputs, nor for calibrating hydrologic models. By combining asynchronous hydroclimatic modelling, an alternative framework designed to construct hydrologic scenarios without resorting to meteorological observations, and quantile perturbation applied to streamflow observations, the proposed workflow produces sound and plausible hydrologic scenarios considering: (1) they preserve trends and physical consistency between simulated climate variables, (2) are implemented from a modelling cascades despite observation scarcity, and (3) support the participation of end-users in producing and interpreting climate change impacts on water resources. The proposed modelling workflow is implemented over four subcatchments of the Chaudière River, Canada, using 9 North American CORDEX simulations and a pool of lumped conceptual hydrologic models. Forced with raw climate model outputs, hydrologic models are calibrated over the reference period according to a calibration metric designed to function with temporally uncorrelated observed and simulated streamflow values. Perturbation factors are defined by relating each simulated streamflow quantiles over both reference and future periods. Hydrologic scenarios are finally produced by applying perturbation factors to available streamflow observations.

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1 Introduction

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Assessments of climate change impacts are commonly oriented in a top-down perspective favoring the implementation of a modelling cascade from climate simulations to impact models (e.g. Poulin et al., 2011; Seiller and Anctil, 2014; Seo et al., 2016). Since climate models are affected by biases that limits their ability to simulate meteorological processes at the local scale, statistical post-processing is typically applied to bias correct (raw) climate model outputs in order to better fit in-situ observations. The end product of a post-processed climate simulation is often termed climate scenario: a plausible trajectory that originally shares the statistical properties of the local (reference) recent past and evolves along physically based long-term trends (Mearns et al., 2001; Huard et al., 2014). Resulting climate scenarios are subsequently translated into simulated streamflow series using calibrated hydrologic models.

The application of statistical post-processed climate model outputs is criticized for three main reasons (e.g. Alfieri et al., 2015b, Chen et al., 2018; Lee et al., 2018): (1) it disrupts the physical consistency between simulated climate variables; (2) it affects the trends in climate change signals imbedded within raw climate simulations; (3) it requires abundant good-quality meteorological observations, which are not available for many regions of the world, including some less common meteorological fields such as wind speed, relative humidity, and radiations (Ricard et al., 2020). More marginal critics raise the fact that statistical post-processing hides raw climate model outputs biases from end-users (Ehret et al., 2012), potentially blurring confidence attributed to resulting impact scenarios, and also, potentially misleading adaptation to climate change. Even if these limitations are generally acknowledged, statistical post-processing is close to be considered as mandatory for climate change impact assessments on water resources. Trend-preserving and multivariate approaches (e.g. Cannon et al., 2018; Nguyen et al., 2020) have been specifically developed in order to limit the above-mentioned post-processing drawbacks. These latter employ, however, a fairly high level of complexification, and consequently, requires specific expertise in post-processing technologies.

In the scientific literature, raw climate model outputs are mostly used as benchmarks to assess the performance issued by post-processed climate model outputs (e.g. Teng et al., 2015; Ficklin et al., 2016; Charles et al., 2020). The use of raw climate model outputs as hydrologic scenarios is a marginal practice, mostly because resulting streamflow simulations are correspondingly affected with biases (e.g. Muerth et al., 2013) and by the lack of synchronicity between the simulated climate and the observed hydrologic (river discharge) time series. The implementation of such an approach is mostly justified considering the use of projections as relative changes to reference conditions (Alfieri et al., 2015a,b) or under the assumption that climate model output biases are sufficiently small to be compensated by the calibration of the hydrologic model (Chen et al., 2013). It is also justified when extreme events are analyzed considering the uncertainty introduced by the short sampling of observation chronicles (Meresa and Romanowicz, 2017).

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Most climate change studies resort to modelling cascades for which hydrologic models are calibrated independently of the climate model outputs, using observations as meteorological forcings (e.g. Poulin et al., 2011; Seiller et al., 2014; Seo et al., 2016). Such approaches are questionable since calibration compensates errors from meteorological observations (e.g. solid precipitation undercatch or spatial interpolation of in-situ observations). It consequently influences the identification of hydrologic model parameters, as well as the representation of hydrologic processes simulated at the catchment scale. The resulting effect on the hydrologic scenarios and projected changes of the water regime components remains mostly misunderstood. Few studies conducted calibration by forcing hydrologic models directly with climate model outputs. Chen et al. (2017) quantified the hydrological impacts of climate change over North America, calibrating a lumped conceptual hydrologic model with raw RCM outputs over a recent past period. Ricard et al. (2020) proposed to calibrate quantile-mapping transfer function concurrently to the parameter of a hydrologic model for meteorological fields for which observations are scarce or unavailable. Both studies operated a calibration with an objective-function that exclude the daily synchronicity of hydrologic events, such as the correspondence between observed and simulated empirical cumulative distribution functions (ecdfs), targeted quantiles, distribution moments, mean flows, or annual cycles.

Here, we propose a straightforward workflow, enabling the production of streamflow projections without post-processing climate model outputs and without using meteorological observations. The procedure is conducted inline with the asynchronous frameworks experimented by Chen et al. (2017) and Ricard et al. (2020). In essence, the proposed workflow translates raw climate model outputs into a corresponding simulated hydrologic response using an asynchronous modelling framework and to encrypt simulated hydrologic changes by defining perturbation factors for each streamflow quantiles. If only relative trends are required, a qualitative climate change impact assessment can be conducted by analysing directly distributions of perturbation factors. If time ordered hydrologic scenarios are required, perturbation factors can be applied to available streamflow observations. Such approach, referred to as quantile perturbation, has been previously applied to climate model outputs (e.g. Sunyer et al., 2014; Willems and Vrac, 2011), but not, to our knowledge, to streamflow simulations resulting from a hydroclimatic modelling cascade.

The key advantage of the proposed workflow is that meteorological observations are not required, nor for post-processing climate model outputs, nor for calibrating the hydrologic model. It is thus easy to implement compared to the conventional modelling cascades, which are typically affected by much heavier requirements in terms of data, modelling processes, and computing capacity. The workflow also preserves trends and consistency between simulated climate variables, and allows a bottom-up assessment of raw climate model outputs from the perspective of the impact modeler and end-users expertise.

The current study aims to display the implementation of the modelling workflow and to demonstrate its applicability by producing time ordered hydrologic scenarios from raw CORDEX simulations over a mid-scale catchment located in Southern Québec, Canada, using a pool of lump conceptual hydrologic models. The study is conducted inline with previous works on

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the innovative asynchronous hydroclimatic modelling framework, the latter being designed to construct hydrologic scenarios without resorting to meteorological observations. Ricard et al. (2019) originally proposed the alternative configuration of the modelling chain and tested five asynchronous objective functions in comparison to a conventional framework. The authors concluded that forcing a physically-based hydrologic model with regional climate simulations according to asynchronous modelling principles can improve the simulated hydrologic response over the historical period. Ricard et al. (2020) implemented statistical post-processing of raw climate model outputs within the asynchronous modelling framework by calibrating quantile mapping transfer functions together with the parameters of the hydrologic model. Authors integrated relative humidity, solar radiation and wind speed to modelling chains and confirmed the improvement of the simulated hydrologic response in comparison to a conventional framework using reanalyses as a description of the reference climate.

2 Methods

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2.1 The Chaudière River catchment

The study is conducted over four subcatchments of the Chaudière River (Fig. 1). This river is 185-km long and takes its source in the Mégantic Lake (altitude 395 m) and flows northward into the Saint-Lawrence River, near Québec City. The 6694-km² catchment is located in the southern part of Province of Québec, Canada, bordering the United States by its meridional delineation. It is shaped by a moderate topography (highest peak is 1100 m), mostly corresponding to the Appalachian geological formation and the Saint-Lawrence Lowlands downstream. The river slope is fairly steep (~2.5 m/km) upstream the town of Saint-Georges (site 4, Fig. 1), and abruptly gentles to ~0.5 m/km down to Saint-Lambert (site 2). The catchment is mostly covered by forest (~70 %), agricultural land uses are nonetheless substantial (~23 %), mostly located in the lower portion of the catchment. The Chaudière River frequently floods from Saint-Georges down to Saint-Lambert and is prone to ice jams mostly around Beauceville (roughly 10 km downstream of Saint-Georges).

The climate of the Chaudière River catchment is humid continental (Dfb according to the Köppen classification). The mean annual temperature shows marked seasonal fluctuations (see Fig. 3), falling below the freezing point roughly from November to March. Total annual precipitation is around 1000 mm, depicting no steep seasonal fluctuations, except for a mild intensification from August to November. The corresponding hydrologic regime can be categorized as nivopluvial, corresponding to an alternance of two dominant flood periods. Driven by snowmelt and rainfall, the main flood period takes place from March to April, while the secondary in autumn is driven by an increase of precipitation. These two flood periods are punctuated by two low flow periods. The flow regime is mostly free from the influence of dam operation, except for short river reaches downstream of Mégantic and Sartigan dams (located at Mégantic Lake and Saint-Georges, respectively).





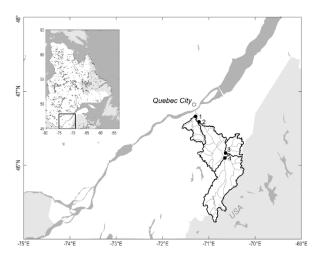


Figure 1: Location of the Chaudière River and subcatchments. Sites 1 to 4 corresponds to hydrometric stations described at Table 1.

Daily discharge observations are collected from the Québec hydrometric network (MELCC, 2021). Stations located at the outlets of the four subcatchments of the Chaudière River are described in Table 1. The four subcatchments encompass 87% of the area of the Chaudière River catchment, only the very downstream part is not being gauged. Station 023402 and 023429 are located on the main river, while 023401 and 023422 are located on the Beaurivage and Famine rivers, two important effluents (709 and 691 km², respectively). Streamflow observational record lengths are fairly long according to North-American standards. 023401 and 023402 are in operation since early 20th Century, while 023422 and 023429, from 1964 and 1969, respectively.

Table 1. Description of Chaudière River subcatchments

Site	Hydrometric station	Location	River	Area (km2)	Data availability
1	023401	Lévis	Beaurivage	709	1925-today
2	023402	Saint-Lambert	Chaudière	5820	1915-today
3	023422	Saint-Georges	Famine	691	1964-today
4	023429	Saint-Georges	Chaudière	3070	1969-today

2.2 Modelling workflow

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The modelling workflow depicted in Fig. 2 aims to produce hydrologic scenarios from raw climate model outputs without resorting to any post-processing of climate model outputs. It does not require meteorological observations for the calibration of the hydrologic models. Instead, an asynchronous calibration loop (Ricard et al., 2020) is implemented forcing the hydrological model with raw climate model outputs over a recent past reference period, translating raw climate model outputs into a corresponding simulated hydrologic response. Since climate models cannot simulate the observed sequence of



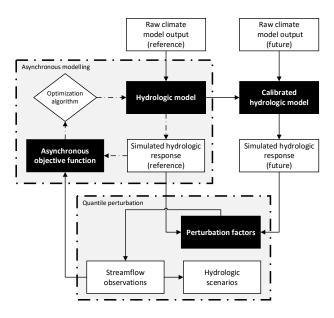
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meteorological events, the simulated hydrologic response is consequently not expected to reproduce the synchronicity of the streamflow observations. Asynchronous calibration draws on objective functions that exclude the day-to-day temporal correlation, referred to as asynchronous objective functions (Ricard et al., 2019). A future hydrologic response is subsequently produced by forcing the calibrated hydrologic models with raw climate change projections.

Hydrologic scenarios are constructed by applying a quantile perturbation to streamflow observations. Perturbation factors are first defined by relating streamflow quantiles issued from the simulated reference and the future hydrologic responses. At this point, the future hydrologic regime can be assessed in terms of relative changes by analyzing perturbation factors for streamflow quantiles of interest. Hydrologic scenarios can also be constructed by applying perturbations factors to available streamflow observations, standing for a plausible trajectory of the water regime conditions, statistically equivalent to the observed recent past that is affected by a physically based long-term trend.



145 Figure 2: Modelling workflow describing the production of hydrologic scenarios from raw climate model outputs. The workflow does not require meteorological observations.

2.3 Climate model outputs

To test the suggested workflow, we used nine North American (NA-) CORDEX simulations (Mearns et al., 2017) that are described in Table 2. They consist of 50-km Regional Climate Models (RCM) simulations that are driven by four Global Climate Models (GCM) forced by the RCP8.5 greenhouse gas (GHG) scenario. 2-meter minimum and maximum air temperature and precipitation were archived over a reference historical period from 1970 to 1999 and a future period from 2040 to 2069.

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Since no statistical post-processing is applied in the proposed modelling workflow, RCM simulations are preferred to GCM simulations in order to minimize the scale mismatch between the climate models and the in-situ observations. RCP8.5 is preferred over RCP4.5 because more NA-CORDEX simulations are then available. Furthermore, the climate change signal is also more pronounced using the RCP8.5 GHG scenario. Since the studied catchment features a topography of moderate complexity and a medium area of 6694 km², a 50-km horizontal resolution was considered sufficient over the finer and less common 25-km simulations. Other climate change impact studies have been conducted with a comparable number of RCM simulations (e.g. Alfieri et al., 2015a,b; Laux et al., 2021).

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Table 2. Description of North American CORDEX simulations

ID	GCM	RCM	Resolution	RCP	Reference period	Future period
crx1	CanESM2	CRCM5				
crx2	CanESM2	CanRCM4				
crx3	CanESM2	RCA4				
crx4	EC-EARTH	HIRHAM5				
crx5	EC-EARTH	RCA4	50 km	8.5	1970-1999	2040-2069
crx6	GFDL-ESM2M	RegCM4				
crx7	MPI-ESM-LR	CRCM5-UQAM				
crx8	MPI-ESM-LR	RegCM4				
crx9	MPI-ESM-LR	WRF				

Figure 3 shows the mean annual cycle of the 2-meter air temperature (2mt) simulated by the 9 NA-CORDEX simulations from 1970 to 1999 over the 023402 subcatchment. Corresponding observations issued by interpolation of in-situ measurements (Bergeron, 2015) and biases are also illustrated. Most climate simulations overestimate 2mt from November to March, the median bias of the ensemble reaching roughly +5 °C in January. NA-CORDEX simulations generally provide a reasonable representation of temperature from May to September, individual biases ranging from -2 °C to +2 °C from one simulation to another. 2mt biases appear to be linked to the forcing GCM simulations. CanESM2-driven simulations (crx1 to crx 3) lead to similar annual profiles marked with an alternance of strong warm winter biases and subsequent moderate warm summer biases. EC-EARTH-driven simulations (crx4 and crx5) show a similar annual profile than CanESM2, but are affected by marked cold spring and summer biases, reaching -5 °C in April in the case of crx4. GFDL-ESM2M-driven simulation (crx6) is affected by a quasi systematic cold bias. MPI-ESM-LR-driven simulations (crx7 to crx9) finally show a constant cold bias from May to November (~-1 °C). The winter warm bias carried by crx7 (CRCM5-UQAM, positive) differ however to the winter cold biases of crx8 and crx9 (RegCM4 and WRF).

Figure 4 shows the mean annual cycle of precipitation simulated by the 9 NA-CORDEX simulations from 1970 to 1999 over the 023402 subcatchment. The ensemble mean overestimates precipitation by roughly +0.5 mm/day. In opposition to 2mt, biases in precipitation are fairly constant throughout the whole annual cycle, except for a brief period in autumn (August to October) where simulations are less biased. Biases typically range between -1 to +2 mm/day depending on the period of the year. Part of the positive bias in winter precipitation can be explained by solid precipitation undercatch, which can reach 20 to 70 % (Pierre et al., 2019). Also, in opposition to 2mt, biases in annual profiles are not as clearly related to the driving GCM.

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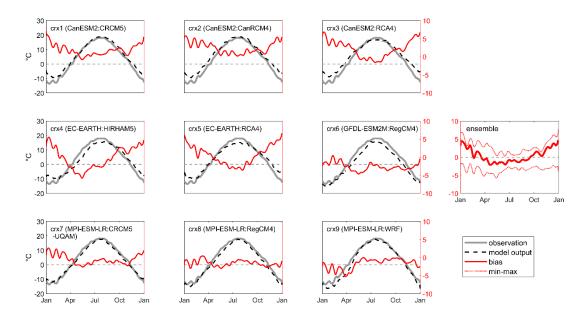


Figure 3: 2-meter air temperature mean annual cycle simulated by the 9 NA-CORDEX simulations (crx1 to crx9) for subcatchment 023402 from 1970 to 1999. Observations and biases are presented. The left scale of the y-axis refers to observations and raw climate model outputs, while the right scale, to biases. A 5-day moving window is applied to all time series in order to enhance the signal to noise ratio. In the ensemble panel, the median, minimum and maximum biases from the 9 climate simulations are illustrated. Observations are derived from kriging in situ data.

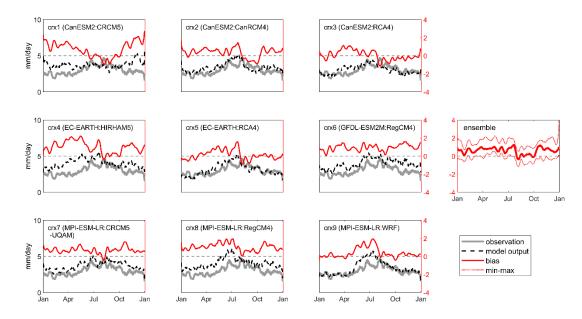
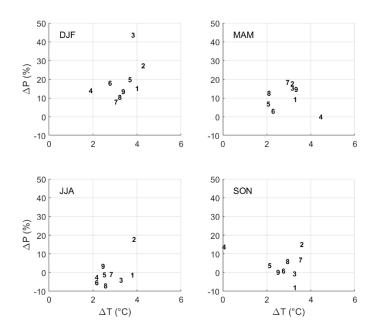


Figure 4: As Fig. 3, but for precipitation.





Figure 5 illustrates seasonal changes (2040-2069 related to 1970-1999) for subcatchment 023402 for the mean 2mt and precipitation from the 9 NA-CORDEX simulations. Increase in 2mt generally falls between +2 and +4 °C. Also, most simulations anticipate precipitation to increase in winter (+10 to +25 %), spring (up to +20 %), and autumn (up to +15 %), but to decrease in summer (down to -10 %). Some simulations show stand-alone outlying trends such as crx3 and crx4 who displays respectively a +44 % increase in winter precipitation and quasi no change in 2mt from September to November.



195 Figure 5: Projected changes (2040-2069 with respect to 1970-1999) of mean 2mt and precipitation from the 9 NA-CORDEX simulations for winter (DJF), spring (MAM), summer (JJA), and autumn (SON) for subcatchment 023402. Numbers refers to the crx simulation described in Table 2.

2.4 Hydrologic modelling

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Table 3 lists the seven lumped conceptual hydrologic models used for simulating the hydrologic response corresponding to the 9 NA-CORDEX simulations. The models are derived from various scientific and operational sources available from the HOOPLA open source MATLAB® toolbox (Thiboult et al., 2019). Models can be categorized as of moderate complexity, the number of open parameters ranging from 6 to 9. All models are combined to the same evapotranspiration formulation (Oudin et al., 2005) and snow module (Valéry et al., 2014), for which the two parameters, thermal inertia of the snowpack (Ctg = 0.25, adimensional) and a degree-day melting factor (Kf = 3.74 mm d⁻¹) are being fixed to default values that are relevant to the region. The selection of hydrologic models is based on the diversity of their structures and their combined performance for short-term streamflow forecasting. The main idea here is to select a pool of heterogenous models in order to avoid that the simulated hydrologic responses are tainted by a single model structure.



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Table 3. Description of the lumped conceptual hydrologic models

ID	Inspired from	No. of parameters	No. of reservoirs
1	CEQUEAU (Girard et al., 1972)	9	2
2	HBV (Bergström and Foreman, 1973)	9	3
3	IHACRES (Jakeman et al., 1990)	7	3
4	MORDOR (Garçon, 1999)	6	4
5	PDM (Moore and Clarke, 1981)	8	4
6	SACRAMENTO (Burnash et al., 1973)	9	5
7	XINANJIANG (Zhao et al., 1980)	8	4

Hydrologic models are calibrated according to an asynchronous modelling framework, i.e. being forced with climate model outputs and excluding the day-to-day temporal correlation (Ricard et al., 2019). The calibration loop is run from 1970 to 1979 with the Shuffle Complex Evolution algorithm (Duan et al., 1993) using 10 complexes. A 10-year period is usually considered sufficiently long for calibration, offering a sound trade-off between identifying representative parametric values and computational requirements. Moreover, since the simulation results displayed in Fig. 6 are produced over a period fairly longer than the calibration period (1970-1999, 30 years), we consider the analysis of the simulated hydrologic response as issued from a functional substitute to the conventional split sample test validation framework. The optimization is run with the *anCRPS* asynchronous metric, minimizing the areas between simulated and observed streamflow empirical cumulative distribution functions (ecdfs) such as:

$$anCRPS(F, x_{obs}) = \int_{-\infty}^{\infty} (F(\tilde{x}) - F(\tilde{x}_{obs}))^2 dx$$
 (1)

220 where \tilde{x} and \tilde{x}_{obs} are respectively the normalized simulated and observed streamflow time series.

$$\tilde{\chi} = \frac{x}{\max(\{x, x_{obs}\})} \tag{2}$$

$$\tilde{x}_{obs} = \frac{x_{obs}}{\max\{\{x, x_{obs}\}\}} \tag{3}$$

Figure 6 shows the simulated seven-model mean annual hydrograph forced by the nine raw NA-CORDEX simulations over the recent past reference period (1970 to 1999) for the subcatchment 023402. Pooled together, simulated hydrographs tend to provide a sound representation of the mean interannual flow in winter, summer, and autumn. The ensemble median bias remains fairly low throughout the year, except for spring where notable misrepresentations is observed in most hydrographs. While some hydrographs show an underestimation of the spring flood magnitude combined to a sound synchronicity, others show a sound representation of the magnitude, but are, on the other hand, affected by a lack of synchronicity in comparison to the observations. The delayed spring flood shown by some hydrographs can be related to simulated 2mt biases in winter and spring (Fig. 3). Some hydrographs carry specific individual seasonal biases such as crx1 and crx2, showing marked winter positive biases, or crx4 and crx8 underestimating mean flow in autumn. Raw NA-CORDEX driven simulated hydrographs



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over other subcatchments of the Chaudière River are presented in appendix and lead to equivalent remarks and explanations. We here remind that the calibration of hydrologic models partially compensates for hydrologic biases (errors in the water budget), but is not expected to correct seasonal fluctuations for two reasons: hydrologic models are not trained in reproducing the observed the annual cycle and the snow routine module parameters have been fixed to default values.

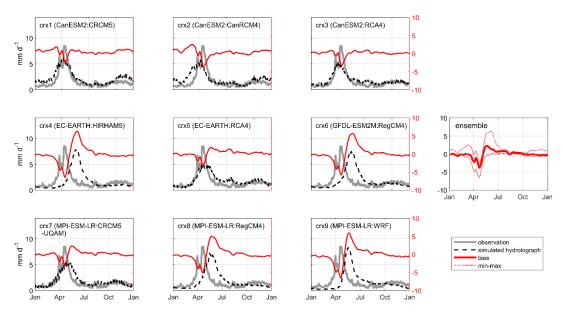


Figure 6: Simulated 7-model mean annual hydrograph forced by the 9 raw NA-CORDEX simulations over the recent past reference period (1970 to 1999) for the subcatchment 023402. Corresponding observations and biases are also illustrated. A 5-day moving window is applied to enhance the signal to noise ratio.

240 2.5 Quantile perturbation

Hydrologic scenarios are produced by applying a non-parametric quantile perturbation (Willems and Vrac, 2011) to streamflow observations. Assuming stationarity of climate model biases, quantile perturbation (see also Willems, 2013; Sunyer et al., 2014; Hosseinzadehtalaei et al., 2018) typically modifies meteorological observations according to relative changes in corresponding distributions projected by raw climate model outputs. Here, change (or perturbation) factors (ϕ) are defined as the ratio between simulated streamflow (Q, associated to the exceedance probability p) from a reference (Ref) to a future (Fut) period, encrypting trends for each streamflow quantiles of, such as:

$$\phi(p,t) = \frac{Q_{Fut}(p,t)}{Q_{Ref}(p,t)} \tag{4}$$

where t refers to a given temporal resolution, i.e. a prior subsampling of the annual cycle for which perturbation factors are evaluated (e.g. bi-annual, seasonal, monthly). $\phi(p,t)$ is subsequently applied to streamflow observations in order to produce hydrologic scenarios, preserving the simulated meteorological trends in all quantiles, including the tails (Cannon et al., 2015).



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Figure 7 shows reference and future streamflow ecdfs issued from the 7-model mean hydrographs for each raw NA-CORDEX simulation. Resulting perturbation factors as prescribed by Eq. (4) are also displayed for each streamflow quantile. ecdfs and perturbation factors are computed according to an annual (no subsampling of the annual cycle) and a biannual (DJFMAM vs JJASON) time period. Here, we justify the biannual resolution based on the typical seasonal fluctuations observed for the nivopluvial hydrologic regime of Southern Québec. Both biannual periods correspond to alternation between low flow and high flow seasonal (nival vs pluvial) hydrologic sub-regimes, both driven by distinct hydroclimatic conditions from one period to the other. Perturbation factors are defined from percentile 0.5 to percentile 99.5 by increments of 1 (100 nodes) and interpolated linearly. Figure 7 shows annual ecdfs depicting little changes in streamflow quantiles from the reference to the future period. Corresponding perturbation factors confirm an increase for lower quantiles (ϕ roughly ranging between 1 and 1.5), while no clear change signal can be observed for higher quantiles. On the other hand, nival ecdfs (DJFMAM) show much more marked fluctuations from reference to future. While all simulations agree on an increase for smaller streamflow quantiles (ϕ ranging between 1 and 2), the shape of perturbation factor distributions change from one simulation to another for intermediate quantiles, ϕ reaching the value of 3 for given simulations and sites. Perturbation factors abruptly decrease for quantiles above 0.9, ranging between 0.8 and 1.3. Changes between reference and future pluvial ecdfs (JJASON) are not as marked as for nival ecdfs. Perturbation factors confirm, however, a consensual decrease for lower streamflow quantiles. The consensus weakens for higher quantiles, corresponding ϕ values being centered around 1. The spread of ϕ values, however, increases for quantiles above 0.8.

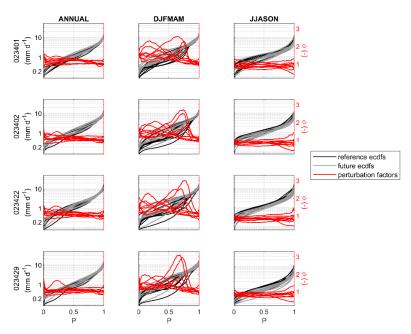


Figure 7: Reference (1970-1999) and future (2040-2069) streamflow ecdfs issued by the nine raw NA-CORDEX simulations and corresponding perturbation factors (φ). Results are shown for subcatchment of the Chaudière River (023401, 023402, 023322, and 023429) and according to an annual and bi-annual (DJFMAM vs JJASON) time periods.





Figure 8 displays the hydrologic scenarios produced over the Chaudière River subcatchments by applying the quantile perturbations to the observed streamflows. It can be seen that the hydrologic scenarios reflect the relative changes embedded within the distributions of perturbation factors shown in Fig. 7. Future winter low flows are systematically higher relative to the observations. Mid-amplitude spring high flows are also affected by notable increases, which is not systematically the case for high-amplitude peak flows. Summer low flows tend to decrease, while summer and autumn high flows are affected by moderate increases and decreases, depending on the scenario.

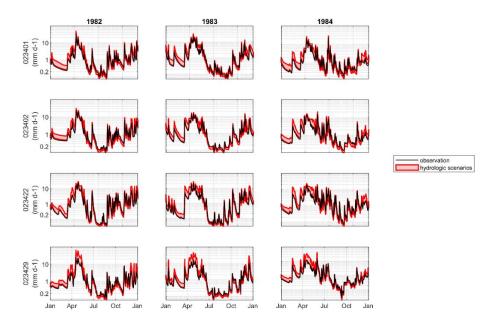


Figure 8: Hydrologic scenarios (in red) produced by applying quantile perturbation to streamflow observations (in black) for each Chaudière River subcatchments (023401, 023402, 023422, and 023429) from 1982 to 1984 (given as example). The min-max red envelope refers to the nine scenarios issued by the raw NA-CORDEX simulations. Note the log axis on the y axis.

3 Discussion

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3.1 A simplified and advantageous hydroclimatic modelling workflow

Nowadays, the quantification of climate change impacts on water resources mostly resorts to the implementation of top-down modelling cascades, translating climate model outputs into simulated hydrologic time series at the catchment scale. Typically, a statistical post-processing is applied to the raw climate model outputs in order to reduce the biases imbedded in the simulated climate variables. Hydrologic models are also typically calibrated when forced by meteorological observations aiming to identify optimal parameter sets minimizing errors between simulated and observed discharge at a given catchment outlet. Assessing the impact of climate change on the hydrologic regime of a catchment using this conventional modelling workflow

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290 presents numerous drawbacks documented in the scientific literature: (1) the statistical post-processing of climate model outputs disrupts the physical consistency between the simulated climate variables, and may even alter the corresponding trends, from a reference to a future period; (2) the modelling work flow is highly relying on the availability and quality of meteorological observations in order to conduct the statistical post-processing of climate model outputs and the calibration of the hydrologic model; and (3) it also requires high level of expertise and computing capacities, restraining the participation of end-users in interpreting and attributing confidence to the simulation results.

In this study, we propose an innovative and quite straightforward hydroclimatic modelling workflow, enabling the production of hydrologic scenarios without resorting to statistical post-processing of climate model outputs. This unconventional approach is conducted using an asynchronous modelling framework, calibrating the hydrologic model forced directly with raw climate model outputs instead of meteorological observations, and using objective-functions that exclude the temporal correlation between the observed and simulated hydrologic responses. Calibrated hydrologic models allow the conversion of raw climate model into corresponding reference and future simulated hydrologic responses. Hydrologic scenarios are subsequently produced by applying quantile perturbations to available streamflow observations, perturbation factors being defined by relating simulated reference and future hydrologic responses for each streamflow quantiles. Quantile perturbation is applied to simulated climate variables such as precipitation or reference evapotranspiration (Ntegeka et al., 2014), but never before, to our knowledge, to the simulated hydrographs resulting from a hydroclimatic modelling cascade.

As opposed to conventional hydroclimatic modelling, the proposed workflow presents numerous benefits: (1) it increases confidence in the hydrologic scenarios since it is conducted with raw climate model outputs, thus preserving physical consistency between simulated climate variables and original trends simulated by the climate models; some authors also argue that raw climate model outputs are expected to improve in resolution and reliability with time (e.g. Teng et al., 2015, Chen et al., 2017); (2) it does not resort to meteorological observations, nor for operating statistical post-processing, nor for calibrating the hydrologic model, facilitating assessment of climate change impact on water resources for regions afflicted with observation scarcity; we would also argue that our approach does not inject uncertainty into the modelling cascade from the intrinsic limitations of post-processing methods (Laux et al., 2021), nor from poor quality observations or reference product describing the reference climate system (Hwang et al., 2014; Kotlarski et al., 2017); (3) it is simple to implement and lighter in computing requirements.

3.2 A bottom-up perspective

Statistical post-processing of climate model outputs suggests a necessary trade-off between key methodological benefits and drawbacks in the scope of providing reliable and supportive information for adaptation to climate change. On one hand, simulated climate variables are corrected to fit statistical properties of the observed climate system. On the other hand, statistical post-processing disrupts physical consistency and alters trends in the simulated climate variables. While designing

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statistical post-processing, a decision is implicitly taken on how these benefits and drawbacks are weighted. In a pure top-down perspective, statistical post-processing is applied according to climate-oriented prerogatives, the end-user rarely being involved in deciding upon which benefit to be prioritized and which drawbacks to be limited. Moreover, not communicating source biases affecting raw climate model outputs constrains the capacity of impact modelers and end-users in assessing the climate model representativeness and attributing confidence to resulting climate scenarios. Nowadays, solutions explored by the scientific community mostly resort to the development of sophisticated post-processing methods. Even though such approaches present undeniable benefits in terms of post-processed physical consistency and trend preservation, we would argue that they further enlarge the gap between climate specialists and water resources end-users, and somewhat restrain adaptation to climate change.

The approach proposed in this study remains in essence a top-down modelling workflow. Through notable simplifications, 330 straightforward constructions between raw climate model outputs and impact models, this alternative framework creates a space for an increased participation of impact modelers and end-users in interpreting climate change impacts on water resources (Ehret et al., 2012). It is thus compatible with integrated and transdisciplinary environmental assessments and modelling frameworks in support to decision and policy making (Hamilton et al., 2015; Rössler et al., 2019). By translating raw climate 335 model outputs into corresponding simulated hydrologic responses, the representativeness of climate models can be assessed in a language impact modelers and end-users can better understand. Based on the simulated hydrologic responses over the reference period (see Mudbhatkal and Mahesha, 2018), key methodological questions can be addressed and debated through an open and empowered dialogue with climate specialists. Questions such as: Are climate outputs representative enough to assess the impacts of climate change on water resources? Should the climatic or hydrologic representation be prioritized? Or 340 both? How should less representative simulations be treated? rejected, weighted (e.g. Shin et al., 2020), or considered equal. Are scenarios required for the adaptation to climate change, or relative change signals sufficient? Should post-processing be applied to raw climate model outputs? We believe decisions upon such questions require a sound understanding of simulated climate forcing, but also an in-depth awareness to requirements and local specificities of the hydrologic system exposed to climate change.

345 **3.3 Limitations**

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We believe the experimental design implemented in this study is sufficient to set a proof-of-concept and demonstrate the applicability of the proposed workflow. To formally asses the impact of climate change on a given domain, a larger ensemble of climate simulations should be considered. Since the workflow does not involve statistical processing of climate model outputs, we would recommend the use of high resolution over coarse gridded climate simulations in order to rely on an improved representation of local scale processes. The use of seven conceptual lumped hydrologic models can also considered as a limitation to our approach. Although they provide a diversity in modelling structure, no formal evaluation of this specific source of uncertainty as been considered in this study (calibration metric, calibration period, structure complexity).

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Assessing the impact of climate change on water resources within the proposed framework implies that the resulting hydrologic scenarios are inevitably tainted with (hydrologic) biases. These biases emerge form raw climate model outputs, but also from the limitations imposed by the structure of the hydrologic models. We believe further works should focus on evaluating how theses two sources are intertwined and how parametric compensation affects the trade-off between hydrologic scenarios fitted to observations and the preservation of the hydrologic change signal embedded within raw climate model outputs. In the meantime, we would argue that parametric compensation should be minimized as much as possible in order to preserve the hydrologic change signal. This could be achieved for example, by restraining parametric spaces during calibration as close as possible to realistic boundaries or favoring physically-based descriptions of hydrologic processes. Even if climate models constantly improve, we call attention to the fact that corresponding biases can still be important and a judgment must be made in order to attribute confidence to resulting hydrologic scenarios. We do not propose here any specific guidelines except that such attribution must consider the scope and objectives of the conducted study and should involve as much as possible climate specialists, impact modelers and end-users.

The proposed workflow is not limited by available meteorological observations, but to available streamflow observations. To assess the impact of climate on water resource to ungauged areas, the modeler can translate the hydrologic perturbation signals under the assumption of representativity of available discharge observation with regards to the ungauged domain. If ungauged streamflow is estimated before applying perturbation factor (using area ratio, hydrological modelling, or optimal interpolation), corresponding uncertainties must by considered.

370 Constructing hydrologic scenarios using the quantile perturbations, our results demonstrated the necessity in identifying a suitable time period to define perturbation factors. Such resolution must consider the specificities of the local flow regime magnitudes. The identification of an optimal time period remains an open question, keeping in mind the use of a moving window could become necessary to compensate breakpoint in the resulting hydrologic scenarios. Even considering the relative change for each streamflow quantiles, the capacity of quantile perturbation to preserve mean flows and seasonal budgets should further be explored and assessed. Further work should also focus on formally comparing our approach to a conventional hydroclimatic modelling framework involving statistical post-processing, analysis the preservation, and consistency for simulated hydrologic variables.





Conclusion

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This study explores an innovative and straightforward modeling workflow enabling the construction of hydrologic scenarios without meteorological observations. The workflow suggests to force hydrologic models with raw climate model outputs and to conduct calibration according to an asynchronous modeling framework. Hydrologic scenarios are finally produced by applying quantile perturbation to available observed streamflow measurements. The workflow is implemented over a midscale catchment located in southern Québec, Canada using an ensemble of NA-CORDEX simulations and a pool of lumped conceptual hydrologic models. Results confirm that biases affecting the raw climate model outputs are propagated throughout the hydroclimatic modeling cascade. They also highlight the importance of considering seasonal fluctuations of the hydrologic regime while applying quantile perturbations to the observed streamflow measurements. We argue that the suggested workflow increases the confidence attributed to the hydrologic scenarios, mostly because it preserves physical consistency between driving simulated climate variables. We also underline that the workflow ease communication between climate experts, impact modelers and end-users, thus supporting decision making in the process of the adaptation of water usages to climate change.

Appendix

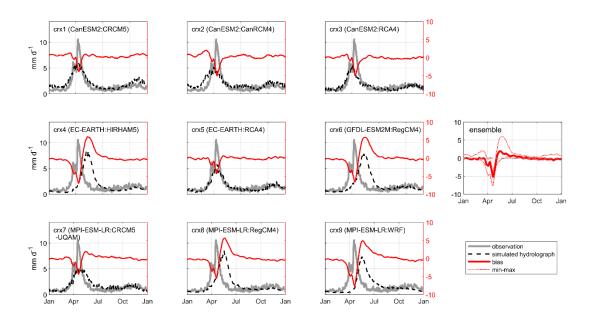


Figure A1: Simulated 7-model mean annual hydrograph forced by the 9 raw NA-CORDEX simulations over the recent past reference period (1970 to 1999) for the subcatchment 023401. Corresponding observations and biases are also illustrated. A 5-day moving window is applied to enhance the signal to noise ratio.





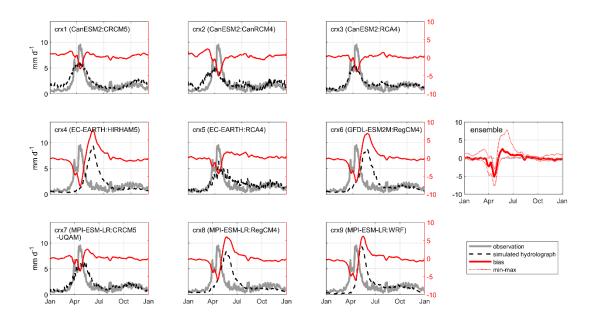


Figure A2: As Fig. A1, but for subcatchment 023422.

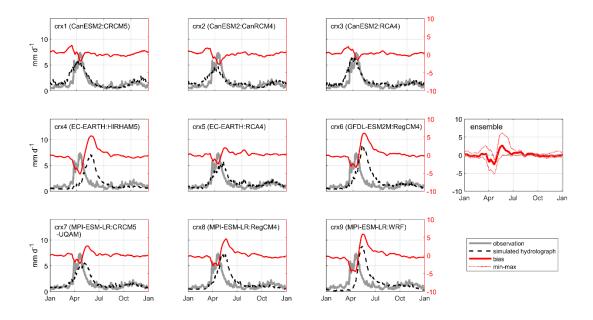


Figure A3: As Fig. A1, but for subcatchment 023429.

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400 Author contribution

SR designed the experiments and SR carried them out. SR developed the model code and performed the simulations. SR prepared the manuscript with significant contributions from co-authors.

Competing interests

The authors declare that they have no conflict of interest.

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References

Alfieri, L., Feyen, L., Dottori, F., and Bianchi, A.: Ensemble flood risk assessment in Europe under high end climate scenarios, Glob. Environ. Change, 35, 199–212, doi:10.1016/j.gloenvcha.2015.09.004, 2015.

Alfieri, L., Burek, P., Feyen, L., and Forzieri., G.: Global warming increases the frequency of river floods in Europe, Hydrol. Earth Syst. Sci., 19, 2247–2260, doi:10.5194/hess-19-2247-2015, 2015.

Bergeron, O.: Grilles climatiques quotidiennes du Programme de surveillance du climat du Québec, version 1.2 – Guide d'utilisation, ministère de l'Environnement et de la Lutte contre les changements climatiques, Québec, Qc., ISBN 978-2-550-73568-7, 33 pp., 2015.

Monger, J. W. H. and Journeay, J. M.: Guide to the geology and tectonic evolution of the southern Coast Mountains, Geol. Surv. of Can., Ottawa, Ont., Open File Rep. 2490, 77 pp., 1994.

Bergström S. and Forsman, A.: Development of a conceptual deterministic rainfall-runoff model, Nord. Hydrol., 4, 147–170, 1973.





- Burnash, R. J. C., Ferral, R. L. and McGuire, R. A.: A generalized streamflow simulation system Conceptual modelling for digital computers, Joint Federal-State River Forecast Center, Sacramento, 1973.
- Cannon, A. J., Sobie, S. R., and Murdock, T. Q.: Bias Correction of GCM Precipitation by Quantile Mapping: How Well Do Methods Preserve Changes in Quantiles and Extremes?, J. Climate, 28, 6938-6959, doi:10.1175/JCLI-D-14-00754.1, 2015.
- 430 Cannon, A. J.: Multivariate quantile mapping bias correction: an N-dimensional probability density function transform for climate model simulations of multiple variables, Clim. Dyn., 50, 31–49., doi:10.1007/s00382-017-3580-6, 2018.
 - Charles, S. P., Chiew, F. H. S., Potter, N. J., Zheng, H., Fu, G., and Zhang, L.: Impact of downscaled rainfall biases on projected runoff changes, Hydrol. Earth Syst. Sci., 24, 2981–2997, doi:10.5194/hess-24-2981-2020, 2020.
- Chen, J., Brissette, F. P., Liu, P., and Xia, J.: Using raw regional climate model outputs for quantifying climate change impacts on hydrology, Hydrol. Process., 31, 4398–4413, doi:10.1002/hyp.11368, 2017.
 - Chen, J., Brissette, F. P., and Chen, H.: Using reanalysis-driven regional climate model outputs for hydrology modelling, Hydrol. Process., 32, 3019–3031, doi:10.1002/hyp.13251, 2018.
 - Duan, Q. Y., Gupta, V. K., and Sorooshian, S.: Shuffled complex evolution approach for effective and efficient global minimization, J. Optim. Theory Appl., 76, 501–521, doi:10.1007/BF00939380, 1993.
- Ehret, U., Zehe, E., Wulfmeyer, V., Warrach-Sagi K. and Liebert, J.: Should we apply bias correction to global and regional climate model data?, Hydrol. Earth Syst. Sci., 16, 3391–3404, doi:10.5194/hess-16-3391-2012, 2012.
 - Ficklin, D. L., Abatzoglou, J. T., Robeson, S. M., and Dufficy, A.: The Influence of Climate Model Biases on Projections of Aridity and Drought, J. Climate, 29(4), 1269-1285, doi:10.1175/JCLI-D-15-0439.1, 2016.
 - Garçon, R.: Modèle global pluie-débit pour la prévision et la prédétermination des crues. La Houille Blanche, 7/8:88–95, 1999.
- 445 Girard, G., Morin, G. and Charbonneau, R.: Modèle précipitations-débits à discrétisation spatiale. Cahiers ORSTOM, Série Hydrologie, 9, 35–52, 1972.
 - Hamilton, S. H., ElSawah, S., Guillaume, J. H. A., Jakeman, A. J., and Pierce, S. A.: Integrated assessment and modelling: Overview and synthesis of salient dimensions, Environ. Model. Softw., 64, 215–229, doi: 10.1016/j.envsoft.2014.12.005, 2015.
- Hosseinzadehtalaei, P., Tabari, H. and Willems, P.: Precipitation intensity–duration–frequency curves for central Belgium with an ensemble of EURO-CORDEX simulations, and associated uncertainties, Atmos. Res., 200, 1–12, doi:10.1016/j.atmosres.2017.09.015, 2018.





Huard, D., Chaumont, D., Logan, T., Sottile, M., Brown, R. D., St-Denis, B. G., Grenier, P., and Braun, M.: A Decade of Climate Scenarios: The Ouranos Consortium Modus Operandi, Bull. Am. Meteorol. Soc., 95, 1213-1225, doi: 10.1175/BAMS-D-12-00163.1, 2014.

Hwang, S., Graham, W. D., Geurink, J. S., and Adams, A.: Hydrologic implications of errors in bias-corrected regional reanalysis data for west central Florida, J. Hydrol., 510, 513–529, doi:10.1016/j.jhydrol.2013.11.042, 2014.

Jakeman, A. J., Littlewood, I. G., and Whitehead, P. G.: Computation of the instantaneous unit hydrograph and identifiable component flows with application to two small upland catchments, J. Hydrol., 117:275–300, doi:10.1016/0022-1694(90)90097-H, 1990.

Kotlarski, S., Szabó, P., Herrera, S., Räty, O., Keuler, K., Soares, P. M., et al.: Observational uncertainty and regional climate model evaluation: A pan-European perspective, Int. J. Climatol., 39, 3730–3749, doi:10.1002/joc.5249, 2017.

Laux, P., Rötter, R. P., Webber, H., Dieng, D., Rahimi, J., Wei, J. et al.: To bias correct or not to bias correct? An agricultural impact modelers' perspective on regional climate model data, Agric. For. Meteorol., 304-305, 108406, doi:10.1016/j.agrformet.2021.108406, 2021.

Lee, M. H., Lu, M., Im, E. S. and Bae, D. H.: Added value of dynamical downscaling for hydrological projections in the Chungju Basin, Korea, Int. J. Climatol., 39, 516-531, doi:10.1002/joc.5825, 2018.

Mearns, L.O., et al.: The NA-CORDEX dataset, version 1.0. NCAR Climate Data Gateway, Boulder CO, doi:10.5065/D6SJ1JCH, 2017 (accessed 30 June 2021).

470 MELCC, Québec Hydrometric Network: https://www.cehq.gouv.qc.ca/hydrometrie/reseau/index.htm/, last access: 15 July 2021.

Meresa, H. K. and Romanowicz, J. R.: The critical role of uncertainty in projections of hydrological extremes, Hydrol. Earth Syst. Sci., 21, 4245–4258, doi:10.5194/hess-21-4245-2017, 2017.

Moore, R. J. and Clarke, R. T.: A distribution function approach to rainfall runoff modelling, Water Resour. Res., 17, 1367–1382, doi:10.1029/WR017i005p01367, 1981.

Mudbhatkal, A. and Mahesha, A.: Bias Correction Methods for Hydrologic Impact Studies over India's Western Ghat Basins, J. Hydrol. Eng., 23, 05017030, doi:10.1061/(ASCE)HE.1943-5584.0001598, 2018.

Muerth, M. J., Gauvin St-Denis, B., Ricard, S., Velázquez, J. A., Schmid, J., Minville, M., et al.: On the need for bias correction in regional climate scenarios to assess climate change impacts on river runoff, Hydrol. Earth Syst. Sci., 17, 1189–1204, doi:10.5194/hess-17-1189-2013, 2013.





Nguyen, H., Mehrotra, R., and Sharma, A.: Assessment of climate change impacts on reservoir storage reliability, resilience, and vulnerability using a multivariate frequency bias correction approach, Water Resour. Res., 56, doi:10.1029/2019WR026022, 2020.

Ntegeka, V., Baguis, P., Roulin, E., and Willems, P.: Developing tailored climate change scenarios for hydrological impact assessments, J. Hydrol., 508, 307–321, doi:10.1016/j.jhydrol.2013.11.001, 2014.

Oudin, L., Hervieu, F., Michel, C., Perrin, C., Andreassian, V., Anctil, F., et al.: Which potential evapotranspiration input for a lumped rainfall-runoff model? part 2 - Towards a simple and efficient potential evapo-transpiration model for rainfall-runoff modelling, J. Hydrol., (303) 290-306. doi:10.1016/j.jhydrol.2004.08.026, 2005.

Poulin, A., Brissette, F., Leconte, R., Arsenault, R. et Malo, J. S.: Uncertainty of hydrological modelling in climate change impact studies in a Canadian, snow-dominated river basin, J. Hydrol., 409, doi:10.1016/j.jhydrol.2011.08.057 626–636, 2011.

Ricard, S., Sylvain, J. D., and Anctil, F.: Exploring an Alternative Configuration of the Hydroclimatic Modeling Chain, Based on the Notion of Asynchronous Objective Functions, Water, 11 (10), doi:10.3390/w11102012, 2019.

Ricard, S., Sylvain, J. D., and Anctil, F.: Asynchronous Hydroclimatic Modeling for the Construction of Physically Based Streamflow Projections in a Context of Observation Scarcity, Front. Earth Sci., 8, doi:10.3389/feart.2020.556781, 2020.

Rössler, O., Fischer, A. M., Huebener, H., Maraun, D., Benestad, R. E., Christodoulides, P., et al.: Challenges to link climate change data provision and user needs: Perspective from the COST-action VALUE, Int. J. Climatol., 39, 3704–3716, doi:10.1002/joc.5060, 2016.

Seiller, G. and Anctil, F.: Climate change impacts on the hydrologic regime of a Canadian river: comparing uncertainties arising from climate natural variability and lumped hydrological model structures, Hydrol. Earth Syst. Sci., 18, 2033–2047, doi:10.5194/hess-18-2033-2014, 2014.

Seo, S. B., Sinha, T., Mahinthakumar, G., Sankarasubramanian, A. and Kumar, M.: Identification of dominant source of errors in developing streamflow and groundwater projections under near-term climate change, J. Geophys. Res. Atmos., 121, 7652–7672, doi:10.1002/2016JD025138, 2016.

Shin, Y., Lee, Y., and Park, J. S.: A Weighting Scheme in A Multi-Model Ensemble for Bias-Corrected Climate Simulation, Atmosphere, 11, 775, doi:10.3390/atmos11080775, 2020.

Sunyer, M. A., Hundecha, Y., Lawrence, D., Madsen, H., Willems, P., Martinkova, M., et al.: Inter-comparison of statistical downscaling methods for projection of extreme precipitation in Europe, Hydrol. Earth Syst. Sci., 19, 1827–1847, doi:10.5194/hess-19-1827-2015, 2015.

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Teng, J., Potter, N. J., Chiew, F. H. S., Zhang, L., Wang, B., Vaze, J., et al.: How does bias correction of regional climate model precipitation affect modelled runoff?, Hydrol. Earth Syst. Sci., 19, 711–728. doi:10.5194/hess-19-711-2015, 2015.

Thiboult A., Poncelet C., and Anctil F.: User Manual : HOOPLA version 1.0.2. Retrieved from https://github.com/AntoineThiboult/HOOPLA, 2019 (accessed 30 June 2021).

Valéry, A., Andréassian, V., and Perrin, C.: As simple as possible but not simpler": What is useful in a temperature-based snow-accounting routine? part 2 - sensitivity analysis of the CemaNeige snow accounting routine on 380 catchments, J. Hydrol., 517, 1176-1187. doi:10.1016/j.jhydrol.2014.04.058, 2014.

Willems, P. and Vrac, M.: Statistical precipitation downscaling for small-scale hydrological impact investigations of climate change, J. Hydrol., 402, 193–205, 10.1016/j.jhydrol.2011.02.030, 2011.

Willems, P.: Revision of urban drainage design rules after assessment of climate change impacts on precipitation extremes at Uccle, Belgium, J. Hydrol., 496, 166–177, doi:10.1016/j.jhydrol.2013.05.037, 2013.

520 Zhao, R. J., Zuang, Y. L., Fang, L. R., Liu, X. R., et Zhang, Q. S.: The xinanjiang model. IAHS Publications, 129: 351–356, 1980.