UNIVERSIDADE FEDERAL DO PARANÁ

CAROLINA NATEL DE MOURA

ASSESSMENT OF THE CLIMATE CHANGE IMPACT UNCERTAINTY CASCADE ON THE RIVER DISCHARGE: A STUDY CASE IN SOUTHERN BRAZIL

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Coorientador: Prof. Dr. Jan Seibert.

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Dedicated to my beloved parents

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RESUMO

Os impactos inevitáveis das mudanças climáticas sobre os recursos hídricos já são visíveis. As principais consequências são o aumento da ocorrência e magnitude de eventos hidrológicos extremos, como cheias e secas, que requerem medidas robustas de adaptação frente às alterações climáticas. A abordagem comum para avaliar os impactos das mudanças climáticas nos recursos hídricos é realizar projeções hidrológicas com base em cenários futuros de modelagem climática. No entanto, existem várias fontes de incerteza nesta metodologia, relacionadas a cenários de emissão, modelos climáticos, correção de viés e modelagem hidrológica. Abordar a incerteza dos impactos das mudanças climáticas na vazão é importante em primeiro lugar para produzir projeções robustas de impactos futuros e, subsequentemente, para apoiar o planejamento de recursos hídricos e a tomada de decisões. Nesta tese, algumas das questões científicas investigadas estão relacionadas a métodos específicos usados na estrutura de análise do impacto das mudanças climáticas na vazão, como o valor agregado da correção de viés na redução de vieses de modelos climáticos, o uso de um método baseado em dados como modelo hidrológico, quantificação da incerteza na vazão projetada e, por fim, como combinar projeções em conjunto. A correção de viés mostrou-se essencial em estudos de mudanças climáticas, sendo a melhor técnica o Mapeamento Empírico de Quantis utilizando fator de correção mensal. O uso de um modelo baseado em dados para previsão de vazão foi menos robusto do que um modelo do tipo balde sob condições de mudança, e deve ser evitado. Os dados de entrada de precipitação usados na modelagem hidrológica impactaram significativamente nas projeções e não devem ser negligenciados na amostragem de incerteza. A variabilidade das projeções do modelo climático foi o contribuinte de incerteza mais significativo na projeção das mudanças na vazão média, seguida pelos dados de entrada de precipitação usados na calibração do modelo hidrológico. A correção de viés e os cenários de emissão contribuíram relativamente pouco para as incertezas totais, enquanto as diferentes parametrizações do modelo hidrológico não contribuíram para a incerteza. Por fim, a busca por um modelo perfeito deve ser substituída por abordagens de modelagem sob-medida (com base na variável de interesse) para minimizar o erro em projeções sob grandes incertezas.

Palavras-chave: Modelo climático. Correção de viés. Modelagem hidrológica. Recursos hídricos. Modelo sob-medida.

ABSTRACT

The unavoidable impacts of climate change on water resources are already visible. The main consequences are the increased occurrence and magnitude of extreme hydrological events, such as floods and droughts, which require robust adaptation measures in the face of climate change. The common approach to assessing the impacts of climate change on water resources is to carry out hydrological projections based on future climate modelling scenarios. However, there are several sources of uncertainty in this methodology, related to emission scenarios, climate models, bias correction, and hydrological modelling. Addressing the uncertainty of climate change impacts on river discharge is important in the first place to produce robust projections of future impacts and subsequently to support water resources planning and decision-making. In this thesis, some of the scientific questions investigated are related to specific methods used in the climate change impact on river discharge framework, such as the added value of bias correction in reducing climate model biases, the use of data-driven methods as hydrological models, quantification of the uncertainty on river discharge and, finally, how to analyse and combine ensemble projections. The bias correction was shown to be essential in climate change studies, the best technique being the Empirical Quantile Mapping using monthly correction factor. The use of data-driven models for river discharge prediction was less robust than a bucket-type model under changing conditions, and should be avoided. The precipitation input data used in the hydrological modelling significantly impacted in the projections, and should not be neglected in uncertainty sampling. The variability of climate model projections was the most significant uncertainty contributor in the projection of changes in the mean river discharge, followed by the precipitation input data used in the hydrological model calibration. Bias correction and emission scenarios contributed relatively little to the total uncertainties, while the different parameterizations of the hydrological model did not contribute to the uncertainty. The search for a perfect model should be replaced by tailor-made (based on interest variable) modeling approaches to minimize the error in projections under large uncertainties.

Keywords: Climate model. Bias correction. Hydrological modelling. Water resources. Purpose-tailored model.

LIST OF MANUSCRIPTS

This thesis is based on the following scientific manuscripts:

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LIST OF ACRONYMS

ANOVA	Analysis of Variance
BESM	Brazilian Earth System Model
BC	Bias Correction
CAMELS-BR	Catchment Attributes and MEteorology for Large-sample Studies – BRazil
CanESM2	Canadian Earth System Model 2
CAPES	Coordination for the Improvement of Higher Education Personnel
CDF	Cumulative Distribution Function
CFSv2	National Centers for Environmental Prediction - Climate Forecast System version 2
CMIP	Coupled Model Intercomparison Project
CO_2	Carbon dioxide
CPC	Climate Prediction Center
DJF	December-January-February
DSST	Differential Split Sample Test
ECMWF	European Centre for Medium-Range Weather Forecasts
EQM	Empirical Quantile Mapping
ES	Emission Scenario
ESKAS	Swiss Federal Commission for Scholarships for Foreign Students
FFP	Fitness-For-Purpose
FOEN	Swiss Federal Office for the Environment
GAP	Genetic Algorithm and Powel optimization
GCM	Global Climate Model
GCM-RCM	Global Climate Model downscaled by Regional Climate Model
GDP	Gross Domestic Product
GHG	Greenhouse Gases
GLEAM	Global Land Evaporation Amsterdam Model
HadGEM2-ES	Hadley Global Environment Model 2 - Earth System
HBV	Hydrologiska Byrans Vattenavdelning
HMI	Hydrological Model Input
HMP	Hydrological Model Parameter
INMET	National Institute of Meteorology
INPE	National Institute of Space Research

IPCC	Intergovernmental Panel on Climate Change
JJA	June-July-August
LS	Linear Scaling
LSTM	Long Short - Term Memory
MAM	March-April-May
MeteoSwiss	Swiss Federal Office of Meteorology and Climatology
MIROC5	Model for Interdisciplinary Research on Climate 5
ML	Machine Learning
MSWEP v2.2	Multi-Source Weighted-Ensemble Precipitation version 2.2
NOAA	National Oceanic and Atmospheric Administration
PRN	Parana
RCM	Regional Climate Model
RCP	Representative Concentration Pathway
RNN	Recurrent Neural Network
SO	Southern Oscillation
SOA	South Atlantic
SON	September-October-November
URU	Uruguay

LIST OF SYMBOLS

P	Precipitation
E	Evaporation
Q	Runoff
S_P	Snow pack
S_M	Soil Moisture
U_Z	Upper ground water zone
L_Z	Lower ground water zone
$lakes$	Volume of lake
P_{sim}^{corr}(t)	simulated precipitation corrected for time t
P_{sim}(t)	simulated precipitation for time t
$\mu_m(P_{obs}(t))$	observed long-term mean precipitation
$\mu_m(P_{sim}(t))$	simulated long-term mean precipitation in the historical period
T_{sim}^{corr}(t)	simulated temperature corrected for time t
T_{sim}(t)	simulated temperature for time t
$\mu_m(T_{obs}(t))$	observed long-term mean temperature
$\mu_m(T_{sim}(t))$	simulated long-term mean temperature in the historical period
p_i^{corr}	i^{th} ranked value of the simulated precipitation corrected
o_i	i^{th} ranked value of the observed precipitation in historical period
$\bar{\Delta}$	mean delta change
Δ_i'	individual delta change
Δ_i	i^{th} ranked delta change [mm]
s_{fi}	simulated precipitation for the future [mm]
s_{ci}	simulated precipitation for the historical period [mm]
$\bar{s_f}$	average of the simulated precipitation for the future [mm]
$\bar{s_c}$	average of the simulated precipitation for the historical period
n	number of observations
A_{me}	Absolute value of the Mean Error
A_{rme}	Relative value of the Mean Error
μ_{sim}	mean of the simulated values
μ_{obs}	mean of the observed values
y_{abs}	absolute precipitation change for the future [mm]
y_{rel}	relative precipitation change for the future [%]

$\mu(P_{sim}^{fut,sce}$(t)	average long-term projected precipitation in a certain future under a chosen scenario [mm]
$\mu(P_{obs}^{baseline}$(t)	average long-term observed precipitation in the reference period (1961 – 1990) [mm]
S_{NR}	Signal-to-noise ratio
N	noise or 'natural variability'
y_{ijk}	climate change signal
μ	mean change
GCM-RCM$_i$	climate model factor, i = Eta-HadGEM2-ES, Eta-MIROC5, Eta-CanESM2 and Eta-BESM
BC_j	Bias correction factor, j = Linear Scaling (yearly correction factor), Linear Scaling (monthly correction factor), Empirical Quantile Mapping (yearly correction factor) and Empirical Quantile Mapping (monthly correction factor)
ES_k	Emission scenario factor, k = RCP 4.5 and RCP 8.5
I_{ijk}	sum of the significant interactions between three factors (climate model, bias correction and emission scenario)
ε_{ijk}	residual error
LS_y	Linear Scaling (yearly correction factor)
LS_m	Linear Scaling (monthly correction factor)
EQM_y	Empirical Quantile Mapping (yearly correction factor)
EQM_m	Empirical Quantile Mapping (monthly correction factor)
i[t]	input gate
σ	logistic sigmoid function
W_i	learnable parameter for the input gate
x[t]	current input
U_i	learnable parameter for the input gate
h[t-1]	last hidden state
b_i	bias vector for the input gate
f[t]	forget gate
W_f	learnable parameter for the forget gate
U_f	learnable parameter for the forget gate
b_f	bias vector for the forget gate
$\bar{c}$[t]	update vector for the cell state with values in the range (-1, 1)
tanh	hyperbolic tangent
W_g	learnable parameter for updating cell state
U_g	learnable parameter for updating cell state
b_g	bias vector for updating cell state
o[t]	output gate

W_o	learnable parameter for the output gate
U_o	learnable parameter for the output gate
b_o	bias vector for the output gate
c[t]	cell memory
$\odot$	element-wise multiplication
c[t-1]	last cell state
h[t]	hidden state
N_{PE}	Non-Parametric Efficiency
N_{SE}	Nash-Sutcliffe Efficiency
K_{GE}	Kling-Gupta Efficiency
M_{ARE}	Mean Absolute Relative Error
FC	Field capacity
LP	Potential Evapotranspiration Limit
BETA	Soil routine parameter
Q_{mean}	Mean discharge
A_{max}	Annual Maximum Discharge
M_{CD}	Maximum Cumulative Deficit

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1 INTRODUCTION

The evaluation of the climate change impacts on water resources is essential to the adaptation planning facing climate change. Studies investigating the impact of climate change on the hydrological response have grown substantially in the last two decades worldwide. Globally, climate change is projected to reduce terrestrial water storage in many regions, especially those in the Southern Hemisphere. An increase is projected in eastern Africa, south Asia and northern high latitudes, especially northern Asia (POKHREL et al., 2021). In South America, major decreases are projected in the annual mean discharge, except for Uruguay Basin where a positive trend is expected (BRÊDA et al., 2020). Rainfall-runoff models combined with emission scenarios from global or regional climate models are widely used to assess the future climate change impacts on the catchment scale. There is a scientific consensus that there are large uncertainties in this modelling framework, mainly composed by emission scenarios, climate modelling, downscaling, bias correction techniques, and impact modelling (BORGES DE AMORIM; CHAFFE, 2019a).

In Brazil, the uncertainty analysis of the climate change impact on water resources is not a common approach. Lots of scientific progress on stressing the importance of the uncertainty sampling, as well as the establishment of initiatives that synchronize efforts among research institutions is needed to sustain better decision making and planning on water resources. Additionally, more practical information on how to deal with these large uncertainties and how to provide reliable estimates to the end-users is still an open scientific question.

1.1 CLIMATE MODELS AND DOWNSCALING

Global Climate Models (GCM) are used to project how anthropogenic emissions influence the planet's climate. These models are the most advanced tool available to simulate the response of the global climate system to the increase in greenhouse gases (GHG) in the atmosphere. GCMs are based on the physical principles of the atmosphere, the oceans and the surface of the planet through established physical laws, such as conservation of mass, energy, and momentum, along with a wealth of observations (STANISLAWSKA; KRAWIEC; KUNDZEWICZ, 2012).

The ability of the models to adequately predict characteristics of the current climate, such as air temperature distributions, atmospheric conditions, precipitation, radiation, wind, temperature and ocean currents, ice cover and main aspects of many of the climate variability patterns can demonstrate the reliability of the long-term projections (RANDALL et al., 2007).

In general, the GCMs are limited in projection capacity to large spatial scales, due to computational constraints, lack of understanding about the phenomenon and the unavailability of detailed observations of some physical processes. This can make it difficult the understanding of important phenomena that occur on smaller scales than the grid resolution of the model. Thus, to carry out projections at the regional level (at the basin scale, for example), it is necessary to use regionalization methods, transforming GCMs into Regional Climate Models (RCM). The regionalization techniques can be divided into two groups of methods: dynamic regionalization and statistic regionalization (HEWITSON; CRANE, 1996).

Dynamic regionalization methods use numerical models as the GCM, but with higher resolution. The most widespread method is the limited area model, formed by equations that describe the atmospheric dynamics of the region to obtain regionalized forecasts (WILBY; WIGLEY, 1997). Statistic regionalization methods use statistical parameters to find relationships between observed regional-scale data and the data generated by GCM on a global scale. These methods are simpler and do not require as much computing capacity as dynamic models (KULIGOWSKI; BARROS, 1998).

Although the scientific and computational advances that has provided major understanding of the climate system and allows the projection of scenarios of climate change, there are still large uncertainty inherent to these projections (NAKICENOVIC et al., 2000), mainly in the regional scale, some variables being more reliable (e.g. temperature) than others (SANTOS et al., 2015).

The main uncertainties in climate modelling are due to the architecture of the numerical model, the spatial discretization of the models and systematic errors caused by the imperfect conceptualization of climate phenomena and processes. Other uncertainty factors are the natural stochasticity and non-linearity of the climate system process, and ignorance of the complete initial condition of the climate system (OLIVEIRA; PEDROLLO; CASTRO, 2015; TEUTSCHBEIN; SEIBERT, 2012).

The use of several climate models with different numerical modelling and conceptualizations in impact studies can help addressing epistemic uncertainties, and the use of GCMs simulations set with several initial conditions can help to deal with the natural variability and aleatory uncertainty. The Intergovernmental Panel on Climate Change (IPCC) considers the results from climate models participating in the Coupled Model Intercomparison Project (CMIP) of the World Climate Research Programme, in which the models are combined to form an ensemble average, giving all models equal weight. Overall, the simple average of the models' output is a better estimate of the real world than any single model (REIFEN; TOUMI, 2009).

1.2 EMISSION SCENARIOS

The GCMs project long-term climate scenarios to provide a basis for how the climate might be in the future (CHOU et al., 2014b). These models are forced by a set of boundary conditions determined by emission scenarios (SAMPAIO; DIAS, 2014). The Fifth Assessment Report on Climate Change (STOCKER, 2013) presented four different scenarios to represent the climatic consequences until the end of the twenty-first century, known as Representative Concentration Pathway (RCP), related to the equivalent concentrations of Carbon Dioxide (CO_2) in the atmosphere. The term 'pathway' emphasizes that not only long-term CO_2 concentration levels are considered, but also the path taken over time to achieve this result, and the term 'representative' means that each RCP provides only one of the many possible scenarios that would lead to specific radiative forcing characteristics (MOSS et al., 2010). The description of the RCP scenarios and the projections until the end of the century are shown in Table 1.1 and Figure 1.1, respectively.

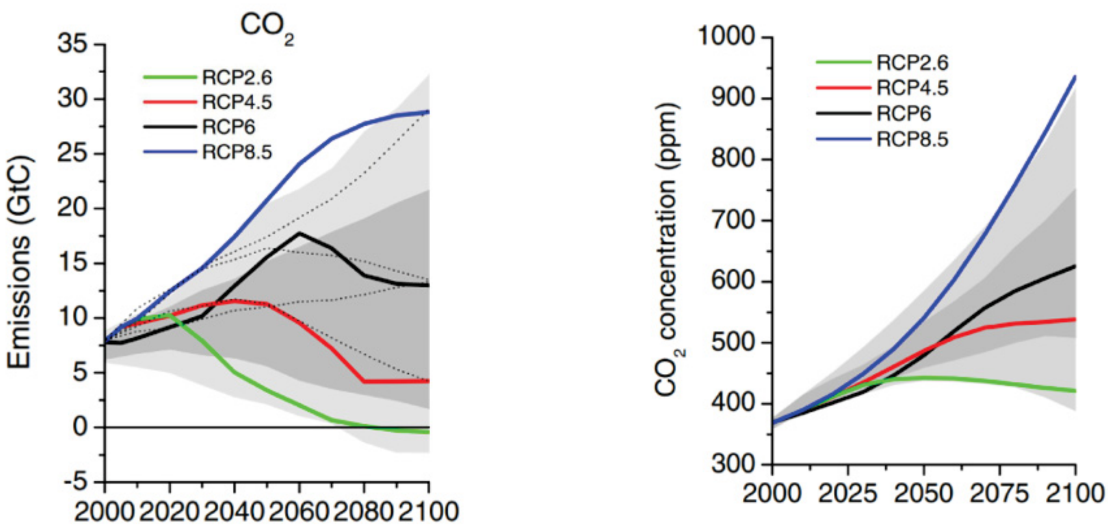
The latest emission scenarios developed and presented in the Sixth Assessment Report on Climate Change (MASSON-DELMOTTE et al., 2021) are called SSP (Shared Socioeconomic Pathways), and expand the RCP scenarios, continuing with energy increase in W/m². They span a larger range of outcomes compared to RCPs, due to higher warming (by close to 1.5°C) reached

Table 1.1: Description of RCP scenarios.

Scenario	Radiative forcing	Concentration (ppm)	Pathway	Model
RCP 8.5	$> 8.5 Wm^{-2}$ in 2100	$>$1,370 CO_2 equiv. in 2100	Increase	MESSAGE
RCP 6.0	$\sim 6 Wm^{-2}$ (with stabilization after 2100)	$\sim$ 850 CO_2 equiv. (with stabilization after 2100)	Estabilization without overcoming	AIM
RCP 4.5	$\sim 4.5 Wm^{-2}$ (with stabilization after 2100)	$\sim$ 650 CO_2 equiv. (with stabilization after 2100)	Estabilization without overcoming	GCAM
RCP 2.6	Peak of $\sim 3 Wm^{-2}$ before 2100 and posterior decline	Peak of $\sim$ 490 CO_2 equiv. before 2100 and posterior decline	Peak and decline	IMAGE

Source: Moss et al. (2010).

Figure 1.1: Global Carbon Dioxide emissions (GtC - Gigatonnes of Carbon per year) (a) under 4 scenarios with different population and economic growth and climate policies and (b) atmospheric concentration of carbon dioxide (parts per million) under 4 scenarios.



(a) (b)

Source: Vuuren et al. (2011).

at the upper end of the 5%–95% envelope of the highest scenario (SSP5-8.5) (TEBALDI et al., 2021).

However, the future emission scenarios are an uncertain factor depending on different hypotheses of socioeconomic growth, demographic change and technological and environmental changes for the planet. They are also subject to uncertainties due to unknown aerosols, volcanic and solar activities, direct effects of increasing atmospheric CO_2 concentration on plants and the effect of behavior of plants in the future climate (MARENGO, 2007).

1.3 BIAS CORRECTION TECHNIQUES

Climate models are subject to a variety of biases that can lead to unreliable projections (SANSOM et al., 2016). As we discussed earlier (Subsection 1.1), the reasons for such biases include systematic model errors caused by imperfect conceptualization, numerical modelling and discretization and spatial averaging within grid cells. Therefore, the climate model simulations usually need to be post-processed to produce reliable estimates (TEUTSCHBEIN; SEIBERT, 2012). The post-processing technique is also called 'bias correction', which usually is based on statistical transformations that adjust the distribution of modelled data such that it closely resembles the observed climatology.

The climate models provide simulations in a historical period that can be used to estimate the differences between simulated and observed values and then compute correction factors to be applied in future series. Bias correction methods have become a standard approach when applying climate model outputs for climate change impact studies at the local and watershed scales (CHEN et al., 2021). Gutiérrez et al. (2019) conducted a very comprehensive study by comparing several bias correction methods for precipitation over Europe, and found that most of the methods were able to reduce the biases of climate model simulations, while none was universally superior to all others. However, several questions are still open regarding appropriateness of bias correction application in hydrological impact studies. The need of the bias correction of climate model outputs is sometimes questioned, since it can affect the consistency between the output variables of the climate model, such as temperature and precipitation (inter-variable dependence) (MUERTH et al., 2013; CHEN et al., 2021), and affect the signal of climate change for the future (EHRET et al., 2012). Additionally, Chen et al. (2013) showed that the performance of hydrological models using raw and corrected climatic variables was dependent on the choice of the bias correction method and location of the catchment, nevertheless the evaluation of different methods before the use in climate change impact studies is rarely taken into consideration (BORGES DE AMORIM; CHAFFE, 2019b). The investigation of the impact of the bias reduction besides the mean and variance (for example in higher statistical moments), in specific purpose variables, as well as the choice of the predictors (whether seasonal or yearly approaches should be preferred) are less investigated.

There are several bias correction techniques, ranging from simple scaling methods to rather sophisticated approaches. Among them, we describe the Linear Scaling and Empirical Quantile Mapping in the following subsections 1.3.1 and 1.3.2, respectively.

1.3.1 Linear Scaling

The Linear Scaling (LS) is a simple method to correct variables based on the observed long-term monthly mean (LENDERINK; BUISHAND; DEURSEN, 2007). Precipitation is corrected multiplying the simulated value by a factor based on the ratio of observed long-term monthly mean and simulated long-term monthly mean in the historical period (Equation 1.1). Air temperature is corrected by adding to the simulated value a term based on the difference of observed and simulated long-term monthly mean (Equation 1.2) The additive version is preferably applicable to unbounded variables (e.g. temperature) and the multiplicative to variables with a lower bound (e.g. precipitation, because it also preserves the frequency).

$$P_{sim}^{corr}(t) = P_{sim}(t). \left[\frac{\mu_m(P_{obs}(t))}{\mu_m(P_{sim}(t))}\right] \tag{1.1}$$

$$T_{sim}^{corr}(t) = T_{sim}(t) + \mu_m(T_{obs}(t)) - \mu_m(T_{sim}(t)) \tag{1.2}$$

Where:
$P_{sim}^{corr}(t)$: Corrected precipitation for time t
$P_{sim}(t)$: Simulated precipitation for time t
$\mu_m(P_{obs}(t))$: Observed long-term monthly mean precipitation
$\mu_m(P_{sim}(t))$: Simulated long-term monthly mean precipitation
$T_{sim}^{corr}(t)$: Corrected air temperature for time t
$T_{sim}(t)$: Simulated air temperature for time t
$\mu_m(T_{obs}(t))$: Observed long-term monthly mean air temperature
$\mu_m(T_{sim}(t))$: Simulated long-term monthly mean air temperature

1.3.2 Empirical Quantile Mapping

The Empirical Quantile Mapping (EQM) calibrates the simulated Cumulative Distribution Function (CDF) by adding to the observed quantiles both the mean delta change and the individual delta changes in the corresponding quantiles (AMENGUAL et al., 2012). This method is applicable to any kind of variable.

The procedure consists of calculating the changes, quantile by quantile, in the CDFs of daily climate model outputs between a historical period and successive future periods (time-slices with the same length of historical). These changes are rescaled on the basis of the observed CDF for the same historical period, and then added, quantile by quantile, to these observations to obtain new calibrated future CDFs that convey the climate change signal, through the following Equations 1.3 - 1.6.

$$p_i = o_i + \bar{\Delta} + \Delta'_i \tag{1.3}$$

Where:
p_i: i^{th} ranked value projected corrected
o_i: i^{th} ranked value observed in historical period
$\bar{\Delta}$: Mean delta change
Δ'_i: Individual delta change

The delta change, the mean delta change and the individual delta change are obtained by the Equations 1.4, 1.5 and 1.6, respectively.

$$\Delta_i = s_{fi} - s_{ci} \tag{1.4}$$

$$\bar{\Delta} = \frac{\sum_{i=1}^{N} \Delta_i}{N} = \frac{\sum_{i=1}^{N} (s_{fi} - s_{ci})}{N} = \bar{s_f} - \bar{s_c} \tag{1.5}$$

$$\Delta'_i = \Delta_i - \bar{\Delta} \tag{1.6}$$

Where:
s_{fi}: Raw future simulated
s_{ci}: Raw historical simulated
Δ_i: i^{th} ranked delta change

N: Number of data points

1.4 HYDROLOGICAL MODELLING

Hydrological modelling is an analysis tool to represent the real-world hydrological system, the behavior of a hydrological process or set of processes, at a given time or time span (MOREIRA, 2005). Hydrological models are used to project the climate change impacts on water resources at basin level from climatic scenarios provided by GCMs and/or RCMs (AMIN et al., 2017; CHILKOTI; BOLISETTI; BALACHANDAR, 2017; ZHANG; XU; FU, 2014). One of the responses of hydrological modelling based on climate change scenarios is the estimation of the future frequency of events important for water resources management, such as low flows that could affect energy production or irrigation systems, as well as floods that can damage infrastructure and impact social communities. The general procedure for simulating the impacts of climate change on hydrological behavior is described below (MUJUMDAR; KUMAR, 2012):

- To determine parameters of a hydrological model for the basin using as input observed climate and flow variables, process called model calibration
- To evaluate the performance of the hydrological model parameters over a portion of historical records which have not been used for the calibration, also called validation
- To project, by GCMs and/or RCMs, future climate variables for the study area
- To simulate the hydrological processes of the basin under the projected climatic conditions
- To compare the simulations of the climatic projections in a reference period to the future period

The uncertainties in the hydrological modelling include errors in model structure, problems in the calibration process and parameterization, and errors in the data used for the calibration (MOGES et al., 2020). In changing conditions, such as in climate change studies, there are also uncertainties regarding the instability of parameters, which may occur due to possible changes in physical characteristics and capture of the dominant processes. The modellers have the crucial task of the choice selection of models, input data, and parameterization methods that may have a significant impact on the magnitude and distribution of the output uncertainty (MOCKLER et al., 2016).

1.4.1 Bucket-type hydrological model

A bucket-type hydrological model consists of several interconnected reservoirs which represents the physical elements in a catchment. The reservoirs or 'buckets' are recharged by rainfall, infiltration and percolation and are emptied by evaporation, runoff, drainage etc. Semi empirical equations are used in this method and the model parameters are estimated not only from field data but also through calibration.

The HBV (Hydrologiska Byrans Vattenavdelning) model is an example of semi distributed bucket-type model (LINDSTRÖM et al., 1997). The HBV model is considered a semi-distributed model since it allows for the catchment to be sub-compartmentalized into different elevation zones, derived from a digital elevation model. The general water balance is presented in Equation 1.7.

$$P - E - Q = \frac{d}{dt}(SP + SM + UZ + LZ + lakes) \tag{1.7}$$

Where P is Precipitation, E is Evaporation, Q is Runoff, SP is Snow pack, SM is Soil moisture, UZ is Upper ground water zone, LZ is Lower ground water zone and $lakes$ represent Volume of lake.

The HBV model simulates catchment discharge, usually on a daily time step, based on time series of precipitation and air temperature as well as estimates of monthly long-term potential evaporation rates. The HBV consists of four routines, the snow routine, the soil routine, the groundwater routine, and the routing routine. In the snow routine, snow accumulation and snow melt are computed by a degree-day method. In the soil routine, groundwater recharge and actual evaporation are simulated as functions of actual water storage. In the response (or groundwater) routine, runoff is computed as a function of water storage. Finally, in the routing routine a triangular weighting function is used to simulate the routing of the runoff to the catchment outlet (SEIBERT; VIS, 2012).

1.4.2 The use of data-driven methods in the hydrological modelling

Data-driven methods are a sub-field of artificial intelligence that is concerned with the design and development of algorithms that allow computers (machines) to improve their performance over time, based on data (MITCHELL et al., 1997). Data-driven models have proven to outperform many hydrological models (e.g., conceptual or physical models) (XU et al., 2020; KRATZERT et al., 2019; NETO et al., 2019; HU et al., 2018; LEE; JUNG; LEE, 2018; DIBIKE; SOLOMATINE, 2001; DAWSON; WILBY, 2001), and the methods are reliable in out-of sample generalization (SHEN, 2018). However little work has been carried out to test the capabilities of data-driven methods to make reasonable predictions under changing conditions or climate change studies. A significant limitation of data-driven models is that they do not benefit from our understanding of physical phenomena and instead rely on the data provided during optimization. Shortridge, Guikema e Zaitchik (2016) argued that data-driven models could only generate reliable predictions for conditions comparable to those experienced historically. Otherwise, the models are likely to introduce considerable uncertainty into their projections.

Nevertheless, the long short-term memory (LSTM), a particular type of recurrent neural network (RNN) (HOCHREITER; SCHMIDHUBER, 1997), has been shown to be promising in capturing the hydrological behaviour from the learning process (XU et al., 2020). Lees et al. (2021) showed that LSTM simulates discharge with consistently high model performance in a large range of catchments in Great Britain, including catchments typically considered difficult to model with four lumped conceptual models. Kratzert et al. (2019) applied the LSTM model over 531 basins over the USA and found a high correlation between the values of the internal cells of an LSTM network and natural processes. In light of the discussion above, testing the robustness of LSTM networks under changing conditions could be interesting to potentially bring hydrological models with different structures in the climate change impact assessment framework.

1.5 UNCERTAINTIES OF THE CLIMATE CHANGE IMPACTS ON PROJECTED DISCHARGE

Several authors have studied the relative importance of the uncertainty sources in climate change impacts on discharge. However the conclusions are still controversial and dependent on variable of interest, time and spatial scale, study region, and uncertainty sampling method. Despite some authors concluded that the global climate model is the most contributor to the total uncertainty (WILBY; HARRIS, 2006; PRUDHOMME; DAVIES, 2009; KAY et al., 2009; ARNELL, 2011; VETTER et al., 2017; KRYSANOVA et al., 2017), the hydrological modelling structure and parameter uncertainty cannot be neglected (BASTOLA; MURPHY; SWEENEY, 2011; BOSSHARD et al., 2013; ZHANG; XU; FU, 2014; GODERNIAUX et al., 2015; DAMS et al., 2015; EISNER et al., 2017; SAMANIEGO et al., 2017; TROIN et al., 2018; ANARAKI et al., 2021). Additionally, the importance of the data input to hydrological models on the uncertainty of model simulations (MERESA et al., 2021; POKORNY et al., 2021) is rarely investigated in climate change impact assessments (TAREK; BRISSETTE; ARSENAULT, 2021). Regarding hydrological modelling, the hydrological model selection (structure) is a major contributor to the overall uncertainty (MOCKLER et al., 2016), however the use and robustness of data-driven methods in climate change assessments should be further investigated.

The uncertainty analysis of the future climate change impacts on the hydrological response are highly important for both hydrological modellers and end-users (water managers, policy-makers). For modellers, uncertainty understanding can lead to better design of the climate change assessment framework, and uncertainty sampling, and for end-users, the quantification of uncertainty is important for guiding the decision-making, either for users wishing to employ robust decision making frameworks or users who are trying to optimize decisions. Especially in Brazil, a major issue in the climate change assessments rely on the methodology, as the use of multi-model ensemble, as well as the evaluation of climate models and the bias correction leave room for improvement (BORGES DE AMORIM; CHAFFE, 2019b; BORGES DE AMORIM; CHAFFE, 2019a; BORGES DE AMORIM; SOUZA; CHAFFE, 2020). Moreover, the practical aspects on how to best combine the ensemble simulations in order to provide realistic projections of climate change on the water resources is an open scientific question.

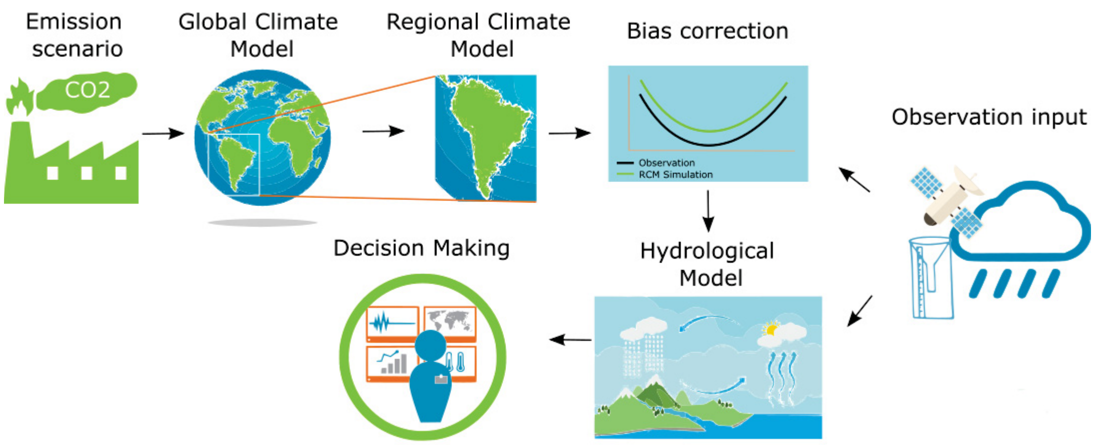
2 SCOPE OF THE THESIS

The understanding of the climate change impacts and uncertainties on water resources is essential for the development of robust adaptation plans and strategies, reducing the risks associated with decisions on water resources. The hypothesis of this work is that uncertainties can significantly influence the magnitude of the climate change impacts projected on discharge. Some of the scientific questions we delved into were:

1. What is the value of the bias correction technique in the climate change assessments framework?
2. Is a data-driven model robust enough for the simulation of future discharge under changing conditions (climate change)?
3. What are the contribution of different sources of uncertainty to the total uncertainty in projected river discharge?
4. Finally, how to deal with large ensembles of simulations in climate change assessments?

In this thesis, we worked in four scientific manuscripts. The paper I was a literature review published as conference proceedings in Portuguese (attached as appendix A). In paper II, we tested the reliability of the Eta Regional Climate Model (RCM) projections in Brazil, the need and performance of several bias correction methods, and the uncertainties in the projected precipitation considering four global climate models downscaled by one RCM, two emission scenarios, and four bias correction techniques. In paper III, we studied the use of a data-driven method as a hydrological model for the application in climate change assessments. Finally, we analysed the propagated uncertainties from emission scenario, climate model, bias correction, and hydrological model input and parameterization to the total uncertainty in projected discharges in Paper IV. As a result, in Chapter 3, we present the main findings of this thesis including answers to the scientific questions, and best practices for modellers and water resources managers.

3 MAIN FINDINGS AND RECOMMENDATIONS FOR MODELLERS AND WATER RESOURCES MANAGERS



1. Bias correction techniques were important to project the impacts of changes in air temperature and precipitation on discharge; Overall, all bias correction methods reduced the error of the climate models, however they had different impacts depending on the purpose-variable. The Empirical Quantile Mapping method should be preferred rather than simple scaling methods Paper II and Paper IV

2. Bucket-type hydrological models are more robust under changing conditions than data-driven models. Before the application of a data-driven models in climate change assessments, robustness tests need to be done to assure the model can generalize for conditions different from the one the parameters were calibrated. Paper III

3. The variability of GCMs-RCM projections was the most significant uncertainty contributor in the projection of changes in the mean discharge, followed by the precipitation input data used in the hydrological model calibration. Bias correction and emission scenarios contributed relatively little to the total uncertainties, while the hydrological model parameters did not contribute to the uncertainty.

   The precipitation input data used to feed hydrological models is an important factor in the hydrological modelling performance and should not be neglected in uncertainty sampling; the use of good quality model-based precipitation data is comparable to ground-level observational data, and could be potentially useful in data-scarce regions. Paper IV

4. Despite the use of ensemble simulations being very computationally expensive, it is crucial to consider the main features that cause considerable uncertainties to minimize considerable risk in water resources management. Seeking the perfect model (or the right model for the right reasons) should be replaced by purpose-tailored modelling approaches to minimize the error in the projections.

   For example, the use of optimized ensemble weights focused on purpose variable (e.g. mean river discharge, maximum discharge or minimum discharge) instead of a single weighting system is a promising approach under deep uncertainty. Paper IV

4 THE IMPACT OF BIAS CORRECTING THE ETA REGIONAL CLIMATE MODEL AND UNCERTAINTIES IN PROJECTED PRECIPITATION OVER NORTH, MIDDLE AND SOUTH BRAZIL - PAPER II

The aim of this paper is answering three main questions: How well the Eta RCM simulate precipitation over three regions in Brazil? What is the impact of bias correction on the reduction of model's biases? (and what is the difference between these methods)? What is the contribution of climate models, bias correction and emission scenarios to the total uncertainty of projected precipitation?

The impact of bias correcting the Eta regional climate model and uncertainties in projected precipitation over North, Middle and South Brazil

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Abstract

Climate change impact assessments performed in Brazil overall lack uncertainty sampling, and climate model performance evaluation, which can lead to unrealistic rainfall projections and, consequently, bad water resources planning and adaptation facing climate change. In this work, we aim to investigate the effect of the bias correction of the last version of the Eta RCM (Regional Climate Model), and the uncertainties in future projected changes by four global climate models downscaled by the Eta RCM (GCM-RCM), four bias correction (BC) techniques and two emission scenarios (ES) using as study case twenty-six rainfall gauge stations located in North, Middle and South Brazil. The performance of raw simulations of the Eta RCM varied spatially over Brazil, being the Amazon the region with the highest biases. The Empirical Quantile Mapping method presented a great impact in the bias reduction, especially when evaluated for multi-day and seasonal precipitation, and it is recommended in impact studies. Great uncertainty levels are attributed to the BC (similar magnitude as GCM-RCM), which indicated that the method should not be neglected in the uncertainty sampling. Projected precipitation changes indicated a decrease in the daily precipitation and extreme precipitation in the Amazon and North and increase in the daily precipitation in Southern Brazil. The precipitation in winter is expected to increase, and under the RCP 8.5 scenario, homogeneously drier conditions were projected for all regions under analysis.

Keywords: climate change assessment, uncertainty analysis, robustness, RCP4.5, RCP8.5

1 Introduction

Climate change is likely to impact precipitation patterns, such as quantity, intensity, frequency and type (Trenberth, 2011), affecting the water availability for food production, power generation and water supply, and increasing the risk of hydrological extremes, such as floods and droughts. The knowledge about the spatial variability and magnitude of changes in rainfall is essential to improve decision-making and increase the adaptability of vulnerable communities under climate change.

Global Climate Models (GCMs) are the main tool to simulate future changes in precipitation due to for example external forcing such as the increase of the greenhouse gases in the atmosphere (Taylor, Stouffer and Meehl, 2011). Due to the coarse resolution of GCMs (grid sizes in the order of 100 km-200 km), a downscaling technique is usually applied to regionalize the simulations to a higher resolution (grid sizes in the order of 20 km), transferring the large-scale information from GCMs to a regional or local scale, resulting in a Regional Climate Model (RCM). However, even after regionalization, RCMs have great biases, which may be corrected using a post-processing technique (or bias correction) (Addor and Seibert, 2014).

Bias correction methods have become a standard approach when applying climate model outputs for climate change impact studies at the local and watershed scales (Chen et al., 2021). Gutierrez et al., 2019 conducted a very comprehensive study by comparing several bias correction methods for precipitation over Europe, and found that most of the methods were able to reduce the biases of climate model simulations, while none was universally superior to all others. However, several questions are still open regarding appropriateness of bias correction application in hydrological impact studies. The need of the bias correction of climate model outputs is sometimes questioned, since it can affect the consistency between the output variables of the climate model, such as temperature and precipitation (inter-variable dependence) (Muerth et al., 2013, Chen et al., 2021), and affect the signal of climate change for the future (Ehret et al., 2012). Additionally, Chen et al., 2013 showed that the performance of hydrological models using raw and corrected climatic variables was dependent on the choice of the bias correction method and location of the catchment. The investigation of the impact of the bias reduction on specific purpose variables, as well as the choice of the predictor (whether seasonal or yearly approaches should be preferred) are also less investigated.

In Brazil, climate change projections largely agree on a precipitation decrease in much of Amazon and Northeast Brazil in the future (Brêda et al., 2020), and increased precipitation in southern Brazil around La Plata basin (Magrin et al., 2014, Malhi et al., 2009; Chou et al., 2014a, 2014b; Ambrizzi et al., 2019). However, climate change assessments conducted in Brazil overall lack addressing the uncertainties inherent to the modelling chain, the use of several GCMs and/or RCMs (multi-model ensemble) is not a common practice, as well as the evaluation of climate models and the effect of bias correction (Borges de Amorim and Chaffe, 2019a, Borges de Amorim and Chaffe, 2019b).

The National Institute for Space Research (INPE) developed four sets of downscaled products based on the Eta RCM for Brazil, parts of South America and adjacent oceans, forced with both RCP 4.5 and RCP 8.5 scenarios of the 5th Assessment Report (AR5) from the IPCC (IPCC, 2013) taken from global simulations and projections from four GCMs, namely HadGEM2-ES, MIROC5, CANESM2 and

BESM, respectively (Chou et al., 2014a). These downscaling simulations are the main projections currently being used in the country for national plans of adaptation to climate changes (Brasil, 2016). The use of Eta model for climate change assessment in South America has shown to be satisfactory for representing monthly precipitation totals and indicate that seasonal variability is reasonably reproduced (Chou et al., 2005), although some areas exhibit systematic biases and overestimates rainfall, especially near mountain regions such as southeastern Brazil (Chou et al., 2012).

Almagro et al. (2020) evaluated the performance of the last version of the Eta RCM nested to two GCM, the British HadGEM2-ES and the Japanese MIROC5, concluding that for most of the Brazilian biomes, the regionalization of the GCMs improved the representation of precipitation, except for the Amazon where the use of the HadGEM2-ES GCM is preferred in relation to the downscaled version, however large biases are still present even after the regionalization. Although large numbers of bias correction methods have been developed, limited comprehensive information is yet available in Brazil for the informed application of the different bias correction approaches for climate change impact and adaptation studies.

In this paper we extended the evaluation of the realiability of the last version of the Eta RCM using the downscaled outputs from the British HadGEM2-ES and the Japanese MIROC5 to the Canadian CANESM2 and the Braziliam BESM models, using ground-level gauge stations in North, Middle and South Brazil. Our study investigated the effect of the bias correction in the improvement of the model simulations of precipitation, taking into account the predictor used in the method (whether yearly or monthly correction factors), the purpose variable (daily minimum, daily maximum and daily mean, monthly and seasonal precipitation), and the time horizon (near and far future). We quantified the individual contribution of three sources of uncertainty in the total uncertainty in projected precipitation, climate model, bias correction and emission scenario.

We argue that understanding the limitations/strengths of the projected simulations, as well as the uncertainty of each element of the modelling chain in the final projection of the variable of interest is essential to firstly bring awareness of the importance of addressing uncertainties in climate change studies and secondly providing guidelines to modellers and end-users. Consequently, resulting in better climate change communication and decision-making and adaptation to climate change.

2 Study area and data

Brazil covers a large area (8,515,767.049 km^2) and has a high rainfall spatial variability, mainly linked to a particular mode of the large-scale variation called the Southern Oscillation (SO). In the northwest, the Amazon basin is characterized by large amounts of rainfall. Together with the Southern Brazil, these regions are the wettest in the country, being the Southern characterized by highly spatially variable rainfall. In Northeast Brazil, the rainfall amount is low with an extensive semiarid area in the interior (Rao and Hada, 1990). Summer is the most common season of high precipitation days in the majority of Brazil, with two main exceptions, part of the coast of Northern Brazil (fall) and Southern Brazil (spring) (Chagas et al., 2020).

We used both ground-level precipitation gauges and projected data by the Eta RCM to study the uncertainties in the projected precipitation over Brazil. The observed precipitation was obtained from the National Institute of Meteorology (INMET; http://www.inmet.gov.br/portal/). From the ‘conventional’ stations (i.e., not automated) available by the INMET (238 in total), we first selected those with data between the period 1961 to 2005. Then, we filtered the gauge stations with less than about 10% of missing data (i.e., less than 2000 missing values), totalizing 26 gauge stations across North, Middle and South Brazil (Figure 1). The main characteristics of the rainfall gauge stations, including gauge id, name, location, altitude and long - term annual precipitation are presented in Table S1 in Appendix B. Missing values were excluded from the analysis, and because of that, each station has a different dataset length, but with at least 90% of data in the period).

The climate projections were obtained from an upgraded version of the Eta RCM (Mesinger et al., 2012), generated by the INPE (National Institute of Space Research). This version of the Eta model was configured in the resolution of 20 km, covering South America, Central America, and Caribbean (Chou et al., 2014a, Chou et al., 2014b). The dynamical downscaling was run using the Eta model on four different Global Climate Models (GCMs), the HadGEM2-ES (Collins et al., 2011), the MIROC5 (Watanabe et al., 2011), the CanESM2 (Chylek et al., 2011) and the BESM (Nobre et al., 2013), described in Table 1. The Eta RCM downscaling procedure is described in more detail in Chou et al. (2014a, 2014b).

The projections were available in two periods: Historical (1961 – 2005) and Future (2006 – 2099). From 2006 the simulations run using the Representation Concentration Pathway (RCP) 4.5 and 8.5 (Chou et al., 2014a). The RCP 4.5 refers to a scenario reaching about 650 ppm of CO_2 equivalent at the end of the century while in the RCP8.5, the equivalent CO_2 exceeds 1000 ppm.

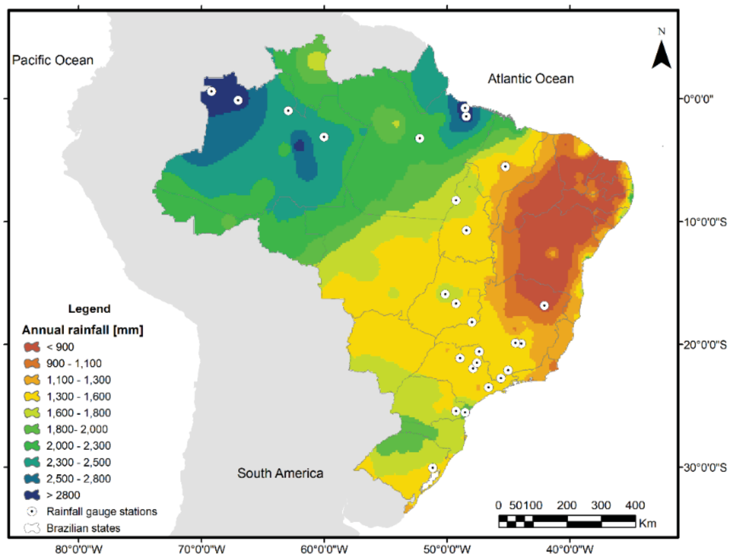


Figure 1. Location of the precipitation gauge stations in Brazil.

Table 1. Global climate model description.

GCM	Full name of GCM	Institution
HadGEM2-ES	Hadley Centre Global Environmental Model version 2 – Earth System	Hadley Centre
MIROC5	Model for Interdisciplinary Research on Climate version 5	Atmosphere and Ocean Research Institute, University of Tokyo, National Institute for Environmental Studies and Japan Agency for Marine-Earth Science and Technology.
CanESM2	Canadian Earth System Model version 2	Canadian Centre for Climate Modelling and Analysis (CCCMA)
BESM - OA 2.5.1	Brazilian Earth System Model	National Institute of Space Research (INPE)

The Eta regional climate model simulations were obtained from <https://projeta.cptec.inpe.br>. Data downloaded on May 1, 2020.

3 Methods

3.1 Bias correction

We applied the Linear Scaling (Lenderink, Buishand and Deursen, 2007) and the Empirical Quantile Mapping (Amengual et al., 2012) under two correction versions: (a) calculating the correction factors on a yearly basis (a single factor for the entire series), and (b) on a monthly basis (one factor per month). We used measured at gauge stations and simulated data in a historical period at the same location for the estimation of the correction factors.

First, we split the historical period (1961 – 2005) data into calibration (80%) and validation period (20%). The calibration period refered to that used for the estimation of the correction factors and the validation period for the evaluation of the bias correction performance. The split was chronological (i.e. without random shuffle), in this way, we also evaluated the ability of the method to be applied in different climate conditions, especially if there was a non-stationarity in the historical period. Once estimated the correction factors based on the differences between observed and simulated data in the calibration period, the correction factors were applied both in the validation period (for the bias correction evaluation) as well as in the future series.

3.1.1. Linear Scaling

The Linear Scaling is a simple method to correct variables based on long-term mean observed (Lenderink, Buishand and Deursen, 2007). Precipitation is corrected by the multiplication of the simulated value by a factor based on the ratio of long-term mean observed and simulated by the model (Equation 1).

$$P_{sim}^{corr}(\mathrm{t}) = P_{sim}(t).\left[\frac{\mu(P_{obs}(t))}{\mu(P_{sim}(t))}\right] \tag{1}$$

Where $P_{sim}^{corr}(\mathrm{t})$ is the simulated precipitation [mm] corrected for time t, $P_{sim}(t)$ is the simulated precipitation for time t [mm], $\mu(P_{obs}(t))$ is the observed long-term mean precipitation in the historical period [mm] and $\mu(P_{sim}(t))$ is the simulated long-term mean precipitation in the historical period [mm].

3.1.2 Empirical Quantile Mapping

The Empirical Quantile Mapping (EQM) corrects the simulated Cumulative Distribution Function (CDF) by adding to the observed quantiles both the mean delta change and the individual delta changes in the corresponding quantiles (Amengual et al., 2012).

The method consists of calculating the changes, quantile by quantile, in the CDFs of daily climate model outputs between historical and successive future periods (time-slices with the same length of historical). These changes are rescaled based on the observed CDF for the same historical period and then added, quantile by quantile, to these observations to obtain new calibrated future CDFs that convey the climate change signal (Equation 2).

$$p_i^{corr} = o_i + \bar{\Delta} + \Delta'_i \tag{2}$$

Where p_i is the ith ranked value of the simulated precipitation corrected, o_i is the it^{h} ranked value of the observed precipitation in historical period, $\bar{\Delta}$ is the mean delta change and Δ'_i is the individual delta change. The delta change, the mean delta change, and the individual delta change are obtained by Equations 3, 4 and 5, respectively.

$$\Delta_i = s_{fi} - s_{ci} \tag{3}$$

$$\bar{\Delta} = \frac{\sum_{i=1}^{n}(s_{fi} - s_{ci})}{n} = \bar{s}_f - \bar{s}_c \tag{4}$$

$$\Delta'_i = \Delta_i - \bar{\Delta} \tag{5}$$

Where s_{fi} is the simulated precipitation for the future [mm], s_{ci} is the simulated precipitation for the historical period [mm], Δ_i is the ith ranked delta change [mm] and n is the number of observations

The 'drizzle effect', which is the common overestimation of wet days by the RCMs (Maraun et al., 2010) was corrected based on a wet-threshold of 1.5 mm.day^{-1}, i.e. the minimum amount of precipitation considered as real precipitation, otherwise, we considered precipitation equals zero.

3.1.3 Statistical evaluation of the model biases and bias correction performance

Biases in climate model simulations are commonly detected by the comparison with observations. Jung (2005) pointed the mean as one of the simplest and most widely used diagnostics to detect climate model biases. Here, the performance of the uncorrected models' simulation and bias correction were evaluated through the Absolute value of the Mean Error (A_{me}) and the Absolute value of the Relative Mean Error (A_{rme}), given by Equation 6 and Equation 7, respectively.

$$A_{me} = |\mu_{sim} - \mu_{obs}| \tag{6}$$

$$A_{rme} = \frac{|\mu_{sim} - \mu_{obs}|}{\mu_{obs}}.100 \tag{7}$$

Where, A_{me} is the estimated mean systematic error over the time period, A_{rme} is the estimated relative mean error over the time period, μ_{sim} is the mean of the simulated precipitation, and μ_{obs} is the mean of the observed precipitation. It's important to point that even if we estimate a A_{me} of zero (i.e., detecting no systematic error), this may be due to error cancelation while calculating the average and even so simulations and observations might be characterized by different variability or distributions (Teutschbein and Seibert, 2013).

It is important to mention that, while mean precipitation is corrected by bias correction by definition, simulations can still be poor for specific precipitation indices like low or high precipitation (Addor and Seibert, 2014). Here, we analyzed several precipitation indices beyond the daily precipitation, in order to evaluate the performance of bias correction in multiday rainfall events, including the low precipitation, defined as the minimum 30-day precipitation amount and the high precipitation, defined as the maximum 4-day precipitation amount. Besides, monthly precipitation, as well as seasonal amounts, were computed (DJF – December, January, February, MAM – March, April, May, JJA – June, July, August, and SON – September, October, November) and analyzed.

3.2 The climate change signal

We analyzed the future changes of precipitation in two periods, the near future (2041 – 2070) and far future (2071 – 2099). The climatological reference normal or baseline (1961 – 1990) was used for computing the changes in the amount of precipitation. This period was chosen because it is a benchmark for climate change assessments (WMO, 2017). The climate change signal or the changes in future precipitation were estimated by the absolute change in millimeters (Equation 8) and the relative change in percentage (Equation 9).

$$y_{abs} = \mu(P_{sim}^{fut,sce}(t)) - \mu(P_{obs}^{baseline}(t)) \tag{8}$$

$$y_{rel} = \frac{\mu\left(P_{sim}^{fut,sce}(t) - \mu(P_{obs}^{baseline}(t))\right)}{\mu(P_{obs}^{baseline}(t))} \cdot 100 \tag{9}$$

Where y_{abs} is the absolute precipitation change for the future (e.g.: near or far) [mm], y_{rel} is the relative precipitation change for the future (e.g.: near or far) [%], $\mu(P_{sim}^{fut,sce}(t))$ is the average long-term projected precipitation in a certain future under a chosen scenario [mm] and $\mu\left(P_{obs}^{baseline}(t)\right)$ is the average long-term observed precipitation in the reference period (1961 – 1990) [mm].

The multi-model ensemble is a well-know approach in climate change assessments in order to address the uncertainties related to models, based on the assertion that no model performs better than another (Borges de Amorim and Chaffe, 2019a). In this study, we chose the ensemble median to estimate the changes in the precipitation, once the median is better suited to describe the average outcome of the ensemble simulations than the mean since outliers do not influence this value.

The robustness of the changes was assessed by the degree of agreement method (Solomon et al., 2007) and signal-to-noise ratio (S_{NR}) (Addor et al., 2014). For the agreement method, it was considered that the direction of a change is 'likely' when 66% or more of all individual model simulations agree in the direction (Mastrandrea et al., 2010). The signal-to-noise ratio was used to measure the significance of the changes when compared with the natural variability of the precipitation.

We adapted the method applied by Addor et al. (2014) for calculating the S_{NR} . The noise (N) or natural variability was estimated by the bootstrapping of the observed precipitation series in the baseline period (1961 – 1990) in 100 subsamples of the same length (30 years) with replacement. Afterwards, we randomly selected 500 pairs from the time series and we estimated the changes between these pairs (i.e. $[x_1 - x_2]$, if absolute change, $\left[\frac{x_1 - x_2}{x_2}\right]$, if relative change). The standard deviation among these 500 relative changes was then used as an estimate of N, considered as the typical change between two time series in absence of climate change, i.e., as a result of climate natural variability over decadal time scales. The S_{NR} was computed then by the ratio between the precipitation change (y) and the noise N, in which a S_{NR} higher than 1 means robust changes for the future, i.e. the signal is identified as significant change and emerges of the natural variability.

3.3 Uncertainty analysis

The variance of the change in precipitation was used as an estimate of the uncertainty. We used the Analysis of Variance (ANOVA) to quantify the contribution of different sources of uncertainty to the final uncertainty. For each one of the chain combinations and future period, we estimated the climate change signal (see Equation 8). The climate change signal was submitted to a log transformation to meet the assumptions of the parametric ANOVA.

The contribution of the different sources of uncertainty to the total uncertainty was quantified by the following model adapted from Addor et al. (2014) (Equation 10).

$$y_{ijk} = \mu + GCM - RCM_i + BC_j + ES_k + I_{ijk} + \mathcal{E}_{ijk} \quad (10)$$

The climate change signal (y_{ijk}) was divided into the mean change μ modulated by the main effects of three factors, the climate model ($GCM - RCM_i$, i = Eta-HadGEM2-ES, Eta-MIROC5, Eta-CanESM2 and Eta-BESM), the bias correction method (BC_j, j = Linear Scaling (yearly correction factor), Linear Scaling (monthly correction factor), Empirical Quantile Mapping (yearly correction factor) and Empirical Quantile Mapping (monthly correction factor), and the emission scenario (ES_k, k= RCP 4.5 and RCP 8.5), as well as the sum of the significant interactions between these factors (I_{ijk}) and the residual error ($\mathcal{E}_{ijk}$).

Interaction effects represent the combined effects of factors on the dependent measure. When an interaction effect is present, the impact of one factor depends on the level of the other factor. Part of the power of ANOVA is the ability to estimate and test interaction effects. As higher-order interactions are hard to physically justify (Addor et al., 2014), we assumed only first-order interactions, i.e., interactions between two factors.

The significance of the main effects and first-order interactions of the ANOVA model was evaluated by the F-test, at the significance level of 0.05. A p-value smaller or equal the significance level (α = 0.05) indicated that the factor and/or interaction uncertainty contribution was significant for the projected precipitation and should be included in the final ANOVA model.

The sum of squares of each element (main effects, interactions, and error term) was divided by the total sum of squares to compute the fraction of variance explained by this element (Von Storch and Zwiers, 2009, Bosshard et al., 2013).

3.4 Experimental design

We combined four GCM-RCM, four bias-corrected simulations and two emission scenarios, in a factorial way, leading to a total of 32 combinations applied in both the baseline (1961 - 1990) and in the two future periods (2041–2070 and 2070–2099) as depicted in Figure 2.

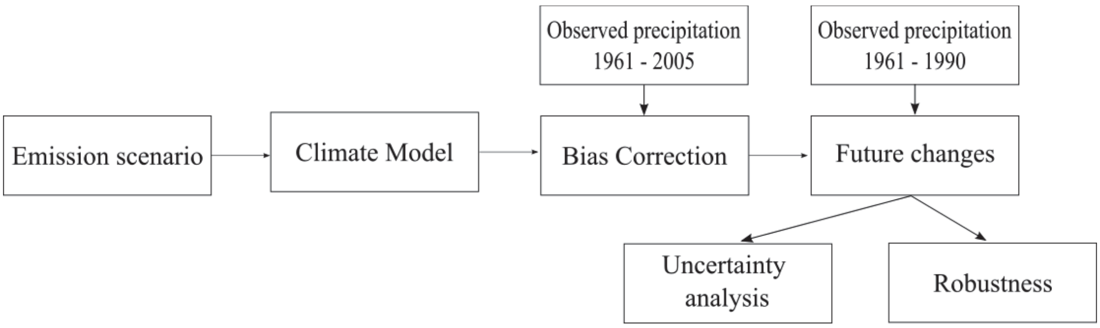


Figure 2. Flowchart of the experimental design. The boxes represent the model chain elements. For each element, several methods were used which are listed under or above the boxes and described in the main text.

4 Results

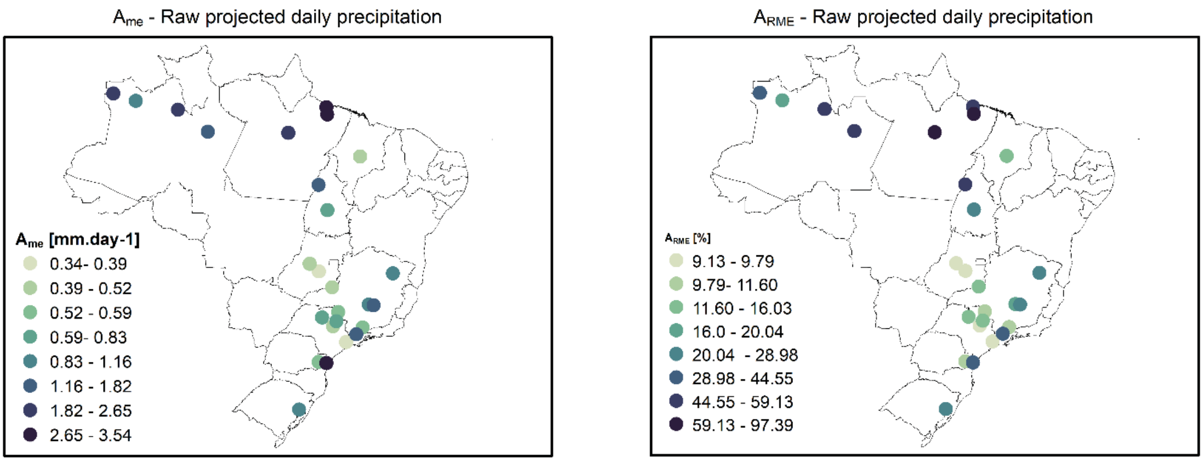
In this section, we address the biases in the RCM outputs and the effect of bias correction methods on the simulated precipitation, the uncertainty contribution of each factor (climate models, bias correction and emission scenarios) in the total uncertainty and the projections of robust changes in precipitation for Brazil.

4.1 Raw climate model simulations and bias correction

There is spatial variability of the uncorrected climate models' biases magnitude across Brazil. The highest raw (uncorrected) simulation biases in millimeters are in the Amazon region, and North Brazil, as well as in one individual gauge station in Southern Brazil (Figure 3a). Coincidentally, these regions are the most humid between the analysed gauge stations. In relative terms (%), the highest biases are located in the Amazon and North region (Figure 3b).

All RCMs have similar performance in average. The climate models' biases range from 0.03 mm to 4.64 mm per day, being in average around 1.33 mm in daily simulations. For the daily and monthly amounts of precipitation, the Eta-HadGEM2-ES model is slightly better than the other models, but for a better understanding of the biases characteristics, see the boxplots for all the precipitation indices in Figure S1 of the Appendix B.

The effect of the bias correction on the reduction of bias in simulated precipitation is presented in Table 2. All bias correction methods improved the raw GCM-RCM simulations. However, the matching between observed and simulated precipitation after the bias correction did not differ significantly between the bias correction methods for the daily and monthly series. Nevertheless, the methods did differ for particularly precipitation indices (low, high and seasonal), being the monthly correction factor version of the LS and EQM better than using a single yearly correction factor. Not surprisingly, there is loss in the BC performance when applying the correction factors estimated in the calibration period on an independent dataset (validation).



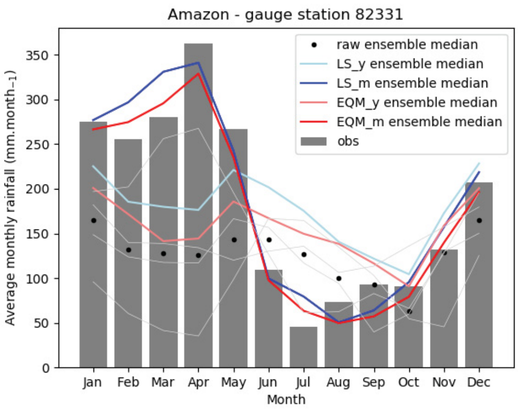
a b

Figure 3. Raw simulations biases from the Eta Regional Climate Model over Brazil. The biases are the average of four RCM-GCMs. (a) Absolute value of the Mean Error (A_{me}); (b) Absolute value of the Relative Mean Error (A_{rme}).

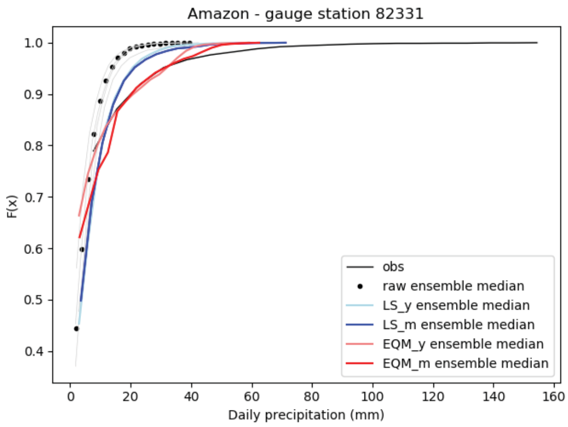
Table 2. Average of the Absolute value of the Mean Error (A_{me}) for the Calibration and Validation period based on 26 precipitation gauge stations before (Raw) and after the bias correction by Linear Scaling (LS) and Empirical Quantile Mapping (EQM) using (yearly (_y) and monthly (_m) factors) .

	Absolute value of the Mean Error [mm]				
	Raw	LS_y	LS_m	EQM_y	EQM_m
Calibration					
Daily [mm.day^{-1}]	1.38	0.00	0.00	0.42	0.54
High [mm.4day^{-1}]	48.76	41.78	39.86	24.49	14.58
Low [mm.30day^{-1}]	11.59	10.89	8.52	11.45	5.08
Monthly[mm.month^{-1}]	41.22	0.00	0.00	1.54	1.09
DJF [mm.season^{-1}]	152.58	107.27	3.74	93.05	6.91
MAM [mm.season^{-1}]	175.71	93.20	2.08	96.74	4.58
JJA [mm.season^{-1}]	132.56	103.09	2.01	91.60	3.84
SON [mm.season^{-1}]	139.39	104.54	2.58	94.27	5.99
Validation					
Daily [mm.day^{-1}]	1.36	0.55	0.60	0.63	0.87
High [mm.4day^{-1}]	42.92	32.78	38.80	22.79	20.34
Low [mm.30day^{-1}]	11.26	10.23	9.45	10.91	7.23
Monthly [mm.month^{-1}]	40.36	16.33	17.19	16.78	17.87
DJF [mm.season^{-1}]	156.18	124.37	68.72	113.20	72.51
MAM [mm.season^{-1}]	198.31	121.79	63.93	122.97	71.43
JJA [mm.season^{-1}]	140.88	123.28	46.78	109.27	52.34
SON [mm.season^{-1}]	149.74	128.28	56.00	118.59	60.66

We show the comparison between observed and simulated long-term monthly precipitation and Cumulative Distribution Function in Figure 4a and Figure 4b, respectively for the validation in a gauge station in the Amazon region (see Figure S2 in Appendix B for other regions).



a



b

Figure 4. Long-term monthly precipitation (a) and Cumulative Distribution Function (b) in validation (1997 – 2005) of observed (obs), raw and bias-corrected by Linear Scaling (LS) and Empirical Quantile Mapping (EQM) (using yearly:_y and monthly: _m correction factors) ensemble median of all the Eta Regional Climate Models (Eta-HadGEM2-ES, Eta-MIROC5, Eta-CanESM2 and Eta-BESM), as well as individual raw climate model simulations in light-grey lines.

4.2 Uncertainty analysis

4.2.1 Daily, high and low precipitation

The main factors (GCM-RCM, BC and ES) and the interactions between these factors (GCM-RCM:ES, GCM-RCM:BC and ES:BC) significance to the total uncertainty are summarised in Figure S3a, Figure S3b and Figure S3c in Appendix B for the daily, high and low precipitation indices, respectively.

The major contribution to the total uncertainty in the daily, high and low precipitation indices correspond to the bias correction, climate model and the interaction between climate model and bias correction, while there is a small contribution due to the emission scenario and interaction between climate model and emission scenario (Table 3).

Table 3. Average variance fraction of the significant main factors and first order interactions in the near and far future per precipitation indice (daily, high and low precipitation). The highest values for uncertainty contributions are in bold.

Future period	Description	Average variance fraction (%)		
		Daily	High	Low
Near	Climate model	**43.58**	21.15	18.1
	Bias correction	40.66	**52.64**	**34.23**
	Emission Scenario	0.6		
	Climate model : Emission Scenario	1.14		
	Climate model : Bias Correction	12.92	23.3	31.34
	Residual	1.1	2.91	19.55
Far	Climate model	34.84	19.96	17.78
	Bias correction	**38.93**	**47.87**	**29.6**
	Emission Scenario	3.07	2.22	6.52
	Climate model : Emission Scenario	4.66		
	Climate model : Bias Correction	14.62	24.59	26.43
	Residual	3.87	5.36	22.76

4.2.2 Seasonal precipitation

According to the F-test (Figure S4), only the main factors climate model, bias correction and interaction between climate model and bias correction were significant in the ANOVA. The variance fractions are presented in Table 4. In general, the bias correction is the main contributor to the total uncertainty of the seasonal precipitations for both near and far future, followed by the interaction between climate model and bias correction.

Table 4. Average variance fraction (η) of the significant main factors and first order interactions in the near (2041 – 2070) and far (2070 – 2099) future per season. The highest values for uncertainty contributions are in bold.

Future period	Description	Average variance fraction (%)			
		DJF	JJA	MAM	SON
Near	Climate model	22.67	9.71	24.66	8.48
	Bias correction	**41.14**	**46.27**	**45.61**	**47.08**
	Climate model : Bias Correction	32.31	37.89	27.19	42.26
	Residual	3.88	6.14	2.54	2.18
Far	Climate model	18.07	8.95	21	7
	Bias correction	**38.4**	41.59	**45.7**	**45.02**
	Climate model : Bias Correction	34.39	**42.27**	26.24	41.05
	Residual	9.14	7.2	7.06	6.93

4.3 Precipitation changes for the future

The robust ensemble median changes are presented in maps showing both the absolute changes on precipitation in millimetres (mm) as well as the relative change in percentage (%). The precipitation changes are composed by the median of all RCMs under analysis after evaluating the robustness by two methods, the degree of agreement method (representing the consistency of the projections), and the S_{NR} (representing the significance of the change compared to the natural variability). In the maps, the size of the bubbles represents the relative change and the colours the absolute changes in millimetres.

4.3.1 Daily, high and low precipitation

The absolute magnitude of the changes for the future is especially higher in the wettest gauge stations under analysis (annual precipitation amounts higher than 1500 mm), as well as the projections are more spread (represented by the width of the boxplot). In relative terms, the changes are homogeneous between the regions. The RCP 8.5 scenarios tend to project stronger drier conditions in general, as well as the far future period projections (Figure S5 – absolute changes and Figure S6 – relative changes).

The precipitation changes corrected by BC methods are correlated to the raw precipitation changes, which suggests that the change signal could be correct even if the magnitude of the changes are not. The Figure 5 shows that in general the changes projected by the raw simulations are stronger (both in terms of increase and decrease in precipitation) than those estimated after bias correction and robustness analysis.

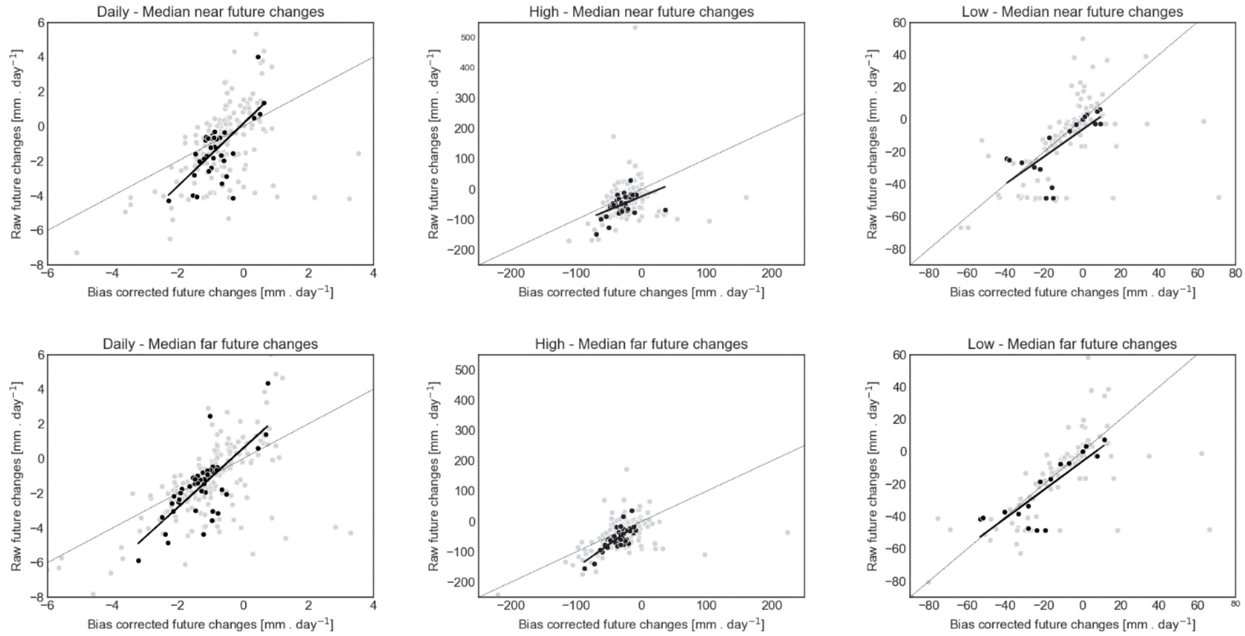


Figure 5. Scatter plot of the bias corrected future changes versus the raw future changes for the daily (first column), high (second column) and low (third column) precipitation indices for the near (first row) and far (second row) future. The grey dots represent the spread of model's simulation, while the black dots represent the robust ensemble median.

The precipitation change is presented in Figure 6a, Figure 7 6b and Figure 6c for the daily, high and low precipitation indices, respectively. Drier conditions are expected for the daily precipitation for North and Central region of Brazil and wetter conditions for Southern Brazil. For the high precipitation indice, the projections indicated a decrease in precipitation. For most of the country, there are non-robust changes for the low precipitation indice, except for an increase in a few stations in North and South Brazil and decrease in the Amazon region.

The near future projections under the RCP 8.5 scenario are similar to the far future scenario under the RCP 4.5 scenario, which lead us to conclude that, earlier or sooner these changes are expected to happen anyways based on the amount of carbon dioxide expected to accumulate in the atmosphere. In the far future and RCP 8.5 scenario, the changes are especially stronger, representing the maximum quantity of carbon dioxide in the atmosphere under these scenarios. For this extreme scenario, an homogeneous decrease in precipitation is projected for the daily, high and low precipitations over the North, Middle and South Brazil.

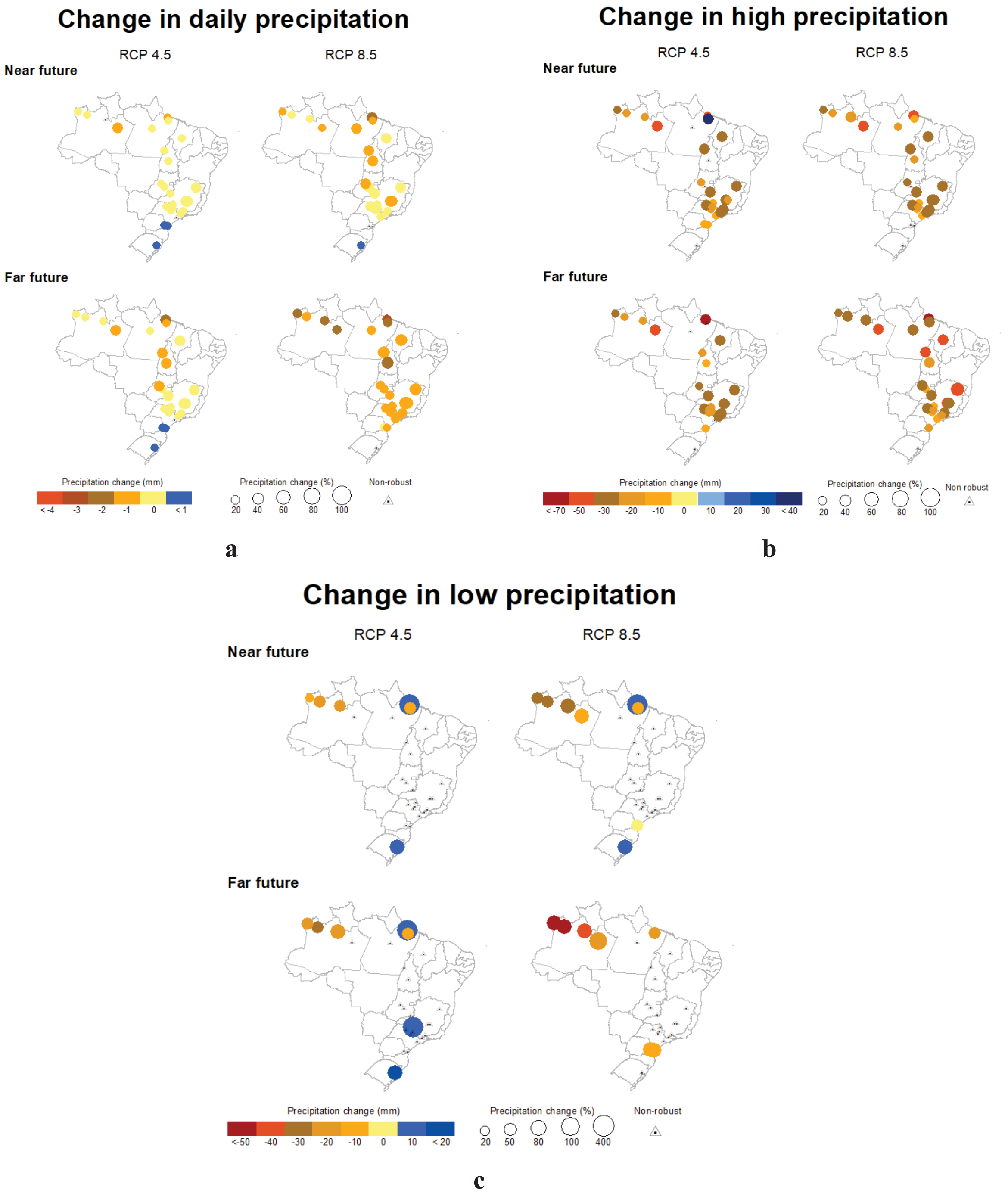


Figure 6. Ensemble median change (mm) in daily (a), high (b) and low (c) precipitation for the near and far future in reference to the baseline (1961 - 1990). The size of the bubbles represents the relative change while the colors represent the absolute change.

There is a positive correlation between the changes for the near and far future (Figure 7a), as well as a positive correlation between the RCP4.5 and RCP8.5 scenarios (Figure 7b). The changes are slightly stronger for the far future, both when the precipitation increases or decreases. Overall, the RCP 8.5

resulted in more significative decreases. The signal of the change usually varies depending on the gauge station (increase or decrease). However, for the high precipitation, there is a declining trend for all the analysed gauge stations.

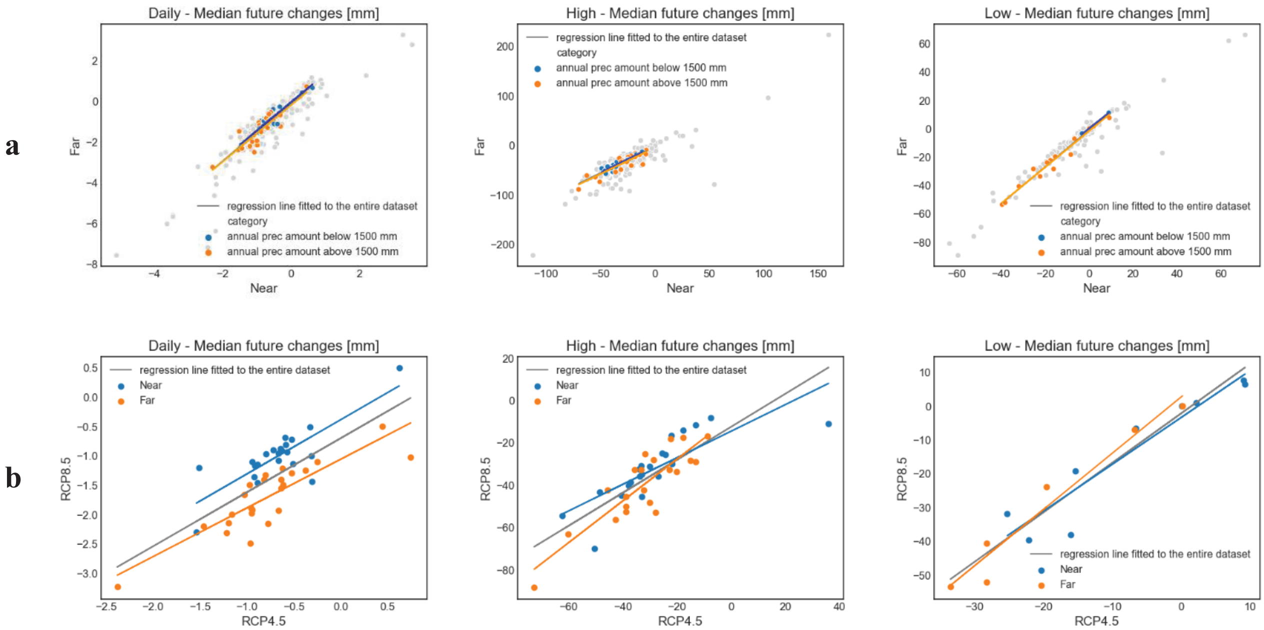


Figure 7. Correlation between near and far future (a) and RCP 4.5 and RCP 8.5 scenarios (b) for the daily, high and low precipitation.

4.3.2 Seasonal precipitation

Stronger absolute changes are expected to the wettest regions in Brazil, and more accentuated in the far future (Figure S7), independently of the season. In contrast, the relative changes are mostly homogeneous over the regions (Figure S8).

The climate models projected mainly decreases in the seasonal precipitations for North and Center region of Brazil and increase for Southern, excepting for the winter (JJA), where most of the regions are expected to have increases in precipitation (Figure 8).

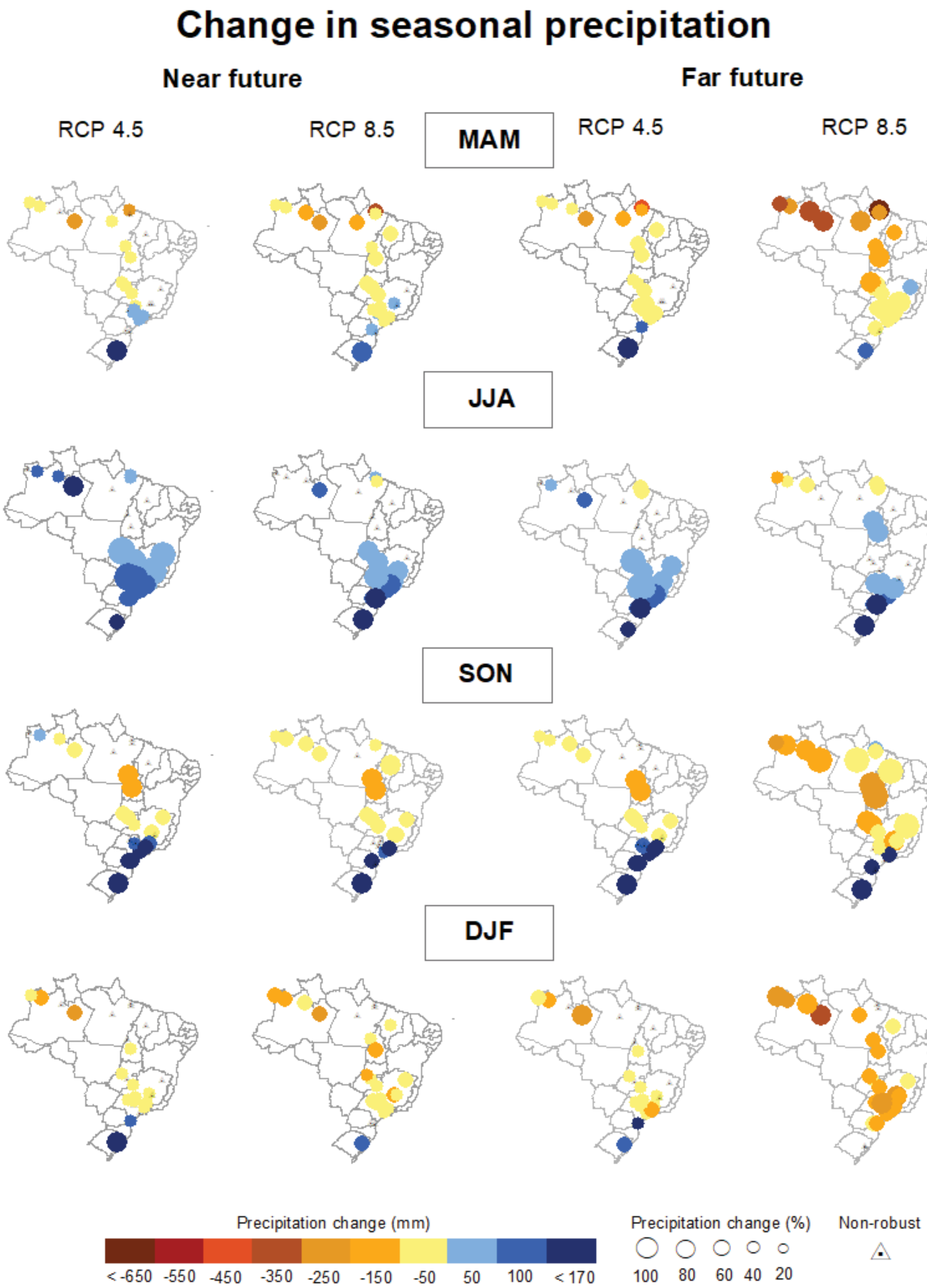


Figure 8. Ensemble median change (mm.season^{-1}) in seasonal precipitation for the near and far future in reference to the baseline (1961 - 1990).

Similar to the daily, high and low precipitation indices, there is a positive correlation between the changes for the near and far future, as well as between the emission scenarios. Usually, the RCP 8.5 presents more significative changes of decreasing. The changes are slightly stronger for the far future, both when the precipitation increases or decreases, but especially for the decreasing projections. The signal of the change usually varies depending on the gauge station (increase or decrease), however, for the gauge stations with precipitation above 1500 mm, the range of the changes is higher.

5 Discussion

5.1 How the bias correction affects the reduction of GCM-RCM biases?

There were great biases in the precipitation projected by the Eta RCMs. After the bias correction, there was a bias reduction in the precipitation indices ranging from -58% (monthly precipitation) to -16% (low precipitation indice). These results emphasise the importance of the implementation of bias correction before applying the simulations of the Eta RCM in Brazil in impact studies (Almagro et al., 2020). There were no significant differences in performance between the methods applied (yearly or monthly correction factor and LS or EQM) for the daily and monthly series, same concluded by Oliveira, Pedrollo and Castro (2015) and Gutiérrez et al. (2019). However the monthly correction factor clearly performed better particularly for seasonal and multiday precipitation indices, as well as for the Amazon region and North Brazil. These results indicate that the choice of the BC method should take into account the purpose variable, and the methods should be evaluated before the careless application in climate change impact frameworks.

5.3 What is the contribution of climate models, bias correction and emission scenarios to the total uncertainty of projected precipitation?

Surprisingly, the variance fraction shows that overall the major contribution to the uncertainty in the projected change in precipitation corresponds to the bias correction, which is an element usually applied in the correction of climate simulations, however neglected in terms of uncertainty sampling (Borges de Amorim and Chaffe, 2019b). The BC participation in uncertainty is followed by the climate model and the interaction between climate model and bias correction, and finally, in a very small proportion, the scenario and interaction between climate model and scenario.

Despite the similar performance of the different BC methods in daily and monthly series, our work indicated that the BC is an important factor depending on the purpose variable, confirming Iizumi et al. (2017), whom also concluded that the participation of bias correction in the total uncertainty is important in the climate change studies of extremes, however not important in the mean climate. The uncertainty analysis indicated that the bias correction should be included in the uncertainty sampling of climate change impact frameworks potentially leading to very different simulations of the impact of the climate change on the precipitation.

5.4 What are the precipitation changes projected over Brazil?

There is high dispersion among the individual model projections for the precipitation change, including incongruence in the signal of the change, in which some models project a negative change while other a positive. This indicates that the choice of the model directly affects the future projection, potentially affecting all the forward climate change cascade of analysis, including the results of impact models. Given that, we highly suggest the use of multimodel ensembles as a way to reduce the uncertainties in future projections, and the implementation of consistency methods rather than only looking at the median of the multi-model ensemble.

The ensemble spread summarises the information about the uncertainties related to the model errors. In this study, we used the ensemble median as a way of contemplating the uncertainty and we performed two robustness tests to evaluate the consistency and significance of the change projections. Most of the changes were considered significant when compared to the natural variability, except for the low precipitation indice, and in general the RCM simulations agreed on the signal of the change.

When the climate change signal of the raw simulations was compared to the bias-corrected simulations, we observed an agreement in the signal of the change (increase or decrease). However, the raw simulations projects stronger changes and since they failed in accuracy in historical period, we would say that they also fail in future magnitude projections.

In general terms, it is projected a reduction in daily precipitation indices in the Amazon region, North and Center region, and an increase in Southern Brazil. Only in the winter season, it is projected a homogeneous increase in precipitation indices over Brazil. For most of the country, there are non-robust changes for the low precipitation indice, except for increase in two individual gauge stations, one in North and one in South Brazil, and decrease in the Amazon region. The major decreases were observed under the RCP 8.5 scenario and far future. The results corroborate to the findings of other studies using different GCM-RCMs projections over Brazil, drier conditions are expected to occur in Brazil in the future.

6 Conclusions

Overall, the RCMs simulations agreed in the signal of the change for North, Middle and South Brazil but fail in accuracy. Thus, bias correction of the raw simulations was demonstrated to be essential in climate change assessments, reducing significantly the models' biases. Our work points to the importance of evaluating bias correction methods in different precipitation indices, since the performance results differ depending on the purpose variable. The EQM is preferred for multi-day precipitation and seasonal precipitation analysis. In terms of uncertainties, the bias correction methods and climate models are the factors that more aggregate uncertainty in the projected precipitations, and the bias correction uncertainty should not be neglected in impact studies.

The future projections of precipitation indicated overall a precipitation decrease for most of the regions under analysis except for an increase in Southern Brazil, confirming the results of other studies in the country. There is a homogeneous increase trend of precipitation in the winter in all regions under analysis.

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5 EVALUATING THE LONG SHORT-TERM MEMORY (LSTM) NETWORK FOR DISCHARGE PREDICTION UNDER CHANGING CLIMATE CONDITIONS - PAPER III

In this paper, we test the predictive ability of the long short - term memory (LSTM) network for discharge prediction under changing climate conditions. To do that, we benchmark the data-driven model over a bucket-type hydrological model; we compare the model performance under changing conditions against a constant condition and we test the impact of the time series size used in calibration on the model performance and robustness.

Evaluating the long short-term memory (LSTM) network for discharge prediction under changing climate conditions

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ABSTRACT

Better understanding the predictive capabilities of hydrological models under contrasting climate conditions will enable more robust decision-making. Here we tested the ability of the long short-term memory (LSTM) for daily discharge prediction under changing conditions using six snow-influenced catchments in Switzerland. We benchmarked the LSTM using the HBV bucket-type model with two parameterizations. We compared the model performance under changing conditions against constant conditions and tested the impact of the time series size used in calibration on the model performance. When calibrated, LSTM resulted in a much better fit than HBV. However, in validation, the performance of the LSTM dropped considerably, and the fit was as good or poorer than the HBV performance in validation. Using longer time series in calibration improved the robustness of the LSTM, whereas HBV needed fewer data to ensure a robust parameterisation. When using the maximum number of years in calibration, LSTM was considered robust to simulate discharges in a drier period than the one used in calibration. Overall, HBV was found to be less sensitive for applications under contrasted climates than the data-driven model. However, other LSTM modelling setups might be able to improve the transferability between different conditions.

Key-words: climate transposability, data-driven model, differential split-sample test, model calibration, model robustness

INTRODUCTION

The use of hydrological models in conditions that differ from those during model calibration is a challenging problem in hydrology, and critical for application in impact studies (Blöschl et al., 2019). Models calibrated in certain conditions have been shown to be not always suitable for different conditions or transferable in time (Pan et al., 2019, Ouermi et al., 2019, Her et al., 2019, Dakhlaoui et al., 2017, Grusson et al., 2017, Broderick et al., 2016, Thirel, Andréassian & Perrin, 2015, Coron et al., 2012, Bastola, Murphy & Sweeney, 2011). The lack of a robust analysis of model performance under changing conditions may lead to poor water resources management.

In the context of catchment hydrology, a changing condition refers to any significant modification in land cover, climate, or water management infrastructure, potentially affecting the transformation of rainfall into runoff (Thirel et al., 2015). A general approach for developing hydrological models suitable for use in transient conditions is to use the Differential Split Sample Test (DSST). The model should be calibrated and validated over contrasting periods in such a method, for instance, calibrated over a wet period and validated during a dry period (Klemes, 1986, Coron et al., 2012). The modeller should seek a good transferability of the calibrated parameters to a different dataset in validation, rather than only a good fit during calibration, which is often translated as model robustness. Robustness is a model's degree of insensitivity to climatic and environmental conditions (Seiller et al., 2012).

Model generalization for contrasting climates has been extensively explored in the literature using the DSST (Seibert, 2003, Wilby, 2005, Vaze et al., 2010, Merz et al., 2011, Coron et al., 2012, Li et al., 2012, Seiller et al., 2012, Brigode et al., 2013, Kling et al., 2015, Li et al. 2015, Seiller et al. 2015, Thirel et al. 2015a, Broderick et al., 2016, Fowler et al., 2016, and Vormoor et al., 2018). The results have shown that model parameters are sensitive to the climatic conditions of the calibration period (Pan et al., 2019), that the transfer of model parameters in time may introduce a significant level of simulation errors (Zhu et al., 2016), and that calibration over a wetter (drier) climate than the validation climate leads to an overestimation (underestimation) of the mean simulated runoff (Coron et al., 2012). Changes in mean rainfall were more likely than changes in mean potential evapotranspiration or air temperature to impact performance during validation (Coron et al., 2012). Furthermore, Broderick et al. (2016) pointed out that the model transferability in contrasted climates may vary depending on the testing scenario, catchment and evaluation criteria. Here we argue that testing new models and new calibration protocols can help with our understanding of the modelling capabilities under changing conditions.

Although data-driven techniques have proven to outperform many traditional approaches based on conceptual or physical models for constant conditions (Xu et al., 2020, Kratzert et al., 2019a, Rafaeli Neto et al., 2019, Hu et al., 2018, Lee et al., 2018, Dibike & Solomatine, 2001, Dawson & Wilby, 1998), and the models are reliable in out-of sample generalization (Shen, 2018), little work has been carried out to test the capabilities of data-driven methods to make reasonable predictions under changing conditions.A significant limitation of data-driven models may be that they do not benefit from our understanding of physical phenomena and instead rely on the data provided during optimization. Shortridge et al. (2016) argued that data-driven models could only generate reliable predictions for conditions comparable to those experienced historically. Otherwise, the models are likely to introduce considerable uncertainty into their projections.

The long short-term memory (LSTM), a particular type of recurrent neural network (RNN), has been shown to be promising in capturing the hydrological behaviour from the learning process (Xu et al., 2020). Lees et al., (2021), showed that LSTM simulates discharge with consistently high model performance in a large range of catchments in Great Britain, including catchments typically considered difficult to model with four lumped conceptual models. Kratzert et al., 2019b applied the LSTM model over 531 basins over the USA and found a high correlation between the values of the internal cells of an LSTM network and natural processes.

Recently, O et al. (2020) evaluated state-of-the-art models to changing conditions, calibrating a LSTM network and two process-based models in 161 catchments distributed across Europe. In their modelling setup, the LSTM model and the process-based models had different calibration approaches. The LSTM was calibrated over all catchments at once using two approaches: calibrating on an extreme reference period (365 days), and calibrating with one randomly selected year from each catchment rather than the respective extreme reference year. In contrast, the process-based models were calibrated in individual catchments and only using the extreme reference period. The models were then used to simulate in the remaining years characterized by a transient condition. The models showed overall performance loss, which generally increased the more conditions deviated from the reference climate, and overall, relatively high robustness was demonstrated by the physically-based model.

In light of the discussion above, in this paper we tested new calibration protocols and extended the scope of the model evaluation, with focus on the LSTM model. This is done by: a) benchmarking the LSTM using the same modelling setup for both data-driven and a process-based model (which includes calibrating one model to each catchment instead of calibrating the LSTM over all catchments), b) testing if increasing the number of years in model calibration would lead to better model performance and robustness, in contrast to only one year used in the previous study), and finally c) calibrating the models in constant conditions as comparison. We then evaluated the robustness of the LSTM for contrasted conditions compared to both its application in constant conditions as well as compared to the robustness obtained by the process-based model.

STUDY AREA AND DATA

For our study, we used six snow-influenced catchments located in Switzerland, ranging from ~ 60 km² to 400 km², with a mean altitude between ~ 500 to 1200 m.a.s.l. The location and description of the catchments (location, area, altitude, daily mean temperature, annual precipitation, mean daily discharge and snow fraction) are presented in Figure 1 and Table 1. Our catchments choice aimed to select catchments mainly located in the Swiss plateau, within a climate homogeneous area, and considered nearly natural (i.e., there is negligible impact on runoff from human activity) (Orth et al., 2015).

The data needed to model the daily discharge were air temperature (°C) and precipitation (mm d^{-1}), and the estimates of long-term monthly potential evapotranspiration (mm $month^{-1}$). Precipitation and air temperature data were obtained from the gridded meteorological forcing data at the spatial resolution of 2 km by 2 km from the Swiss Federal Office of Meteorology and Climatology (MeteoSwiss). We obtained daily discharge measurements from the Swiss Federal Office for the Environment (FOEN).

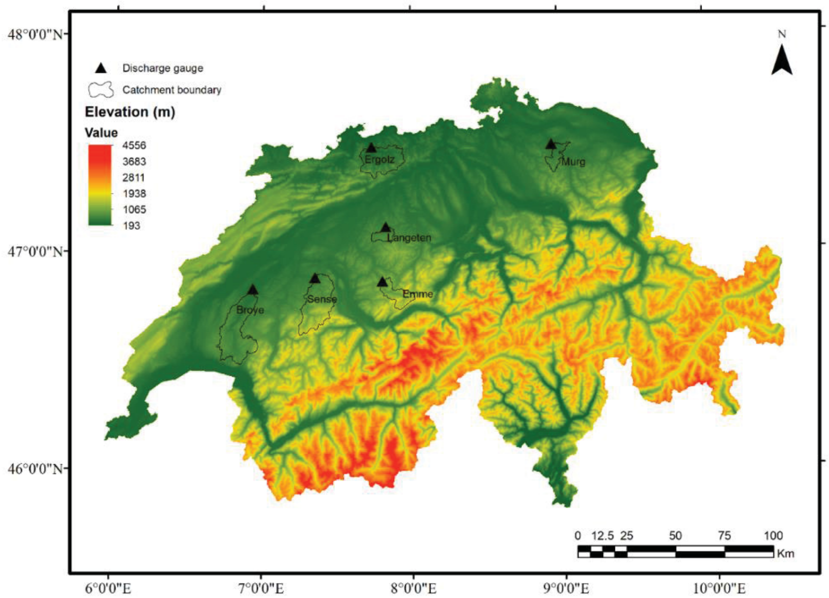


Figure 1. Location of the study catchments

Table 1. Properties of the study catchments

Catchment	Mean altitude (m)	Area (km^2)	Daily mean temperature (°C)	Total Precipitation (mm $year^{-1}$)	Mean discharge (mm d^{-1})	Snow fraction[(i)] (%)
Broye	710	392	8.6	1190	1.6	5
Emme	1189	124	5.6	1692	3.0	19
Ergolz	590	261	8.6	1091	1.2	6
Langeten	766	60	7.5	1305	1.8	10
Murg	650	79	8.0	1313	2.0	7
Sense	1068	352	6.3	1445	2.1	13

[(i)] Snow Fraction (%): fraction of precipitation falling with temperature below 0°C.

METHODS

LSTM

The LSTM is a particular type of RNN used to process long time-sequences of data (Hochreiter & Schmidhuber, 1997) in which the output of each time step is fed as input to the next time step. The control of the information flow is managed in units called gates and memory cells. The cell remembers values over arbitrary time intervals, and three gates regulate the flow of information into and out of the cell: the forget gate, the input gate and the output gate. At every time-step t, each of the three gates is presented with the input $x[t]$ (i.e., explanatory variables) as well as the output $h[t-1]$ of the memory cells at the previous time-step $[t - 1]$.

The first gate is the forget gate, which controls what information is removed from the cell state vector (Equation 1). The hidden state h is initialized in the first time step by a vector of zeros. In the next step, a potential update vector for the cell state is computed from the current input $x[t]$ and the last hidden state $h[t-1]$ by Equation 2. Additionally, the second gate is computed, the input gate (Equation 3), defining which (and to what degree) information of $\bar{c}[t]$ is used to update the cell state in the current time step. With the results of the forget gate and input gate, the cell state $c[t]$ is updated by Equation 4. Like the hidden state vector, the cell state is initialized by a vector of zeros in the first time step. The last gate is the output gate, which controls the information of the cell state $c[t]$ that flows into the new hidden state $h[t]$. The output gate is calculated by Equation 5. Finally, the hidden state $h[t]$ is calculated using the current cell state and the output gate value (Equation 6). The model output is a linear combination of hidden states at the last time step (Kratzert et al., 2018).

$$f[t] = \sigma(W_f x[t] + U_f h[t-1] + b_f) \quad (1)$$

$$\bar{c}[t] = tanh(W_g x[t] + U_g h[t-1] + b_g) \quad (2)$$

$$i[t] = \sigma(W_i x[t] + U_i h[t-1] + b_i) \quad (3)$$

$$c[t] = f[t] \otimes c[t-1] + i[t] \otimes \bar{c}[t] \quad (4)$$

$$o[t] = \sigma(W_o x[t] + U_o h[t-1] + b_o) \quad (5)$$

$$h[t] = o[t] \otimes tanh\,(c[t]) \quad (6)$$

Where$f[t]$, $i[t]$ and $o[t]$ are the forget, input and output gates represented by vectors with values in the range (0, 1), $\bar{c}[t]$ is a vector with values in the range (−1, 1), $x[t]$ is the input vector (forcings and static attributes), $tanh$ (·) is the hyperbolic tangent, σ (·) represents the logistic sigmoid function, $\otimes$ denotes element-wise multiplication, and Ws, Us and bs are sets of learnable parameters., i.e., two adjustable weight matrices and a bias vector.

In this work, we used a network consisting of a single LSTM layer with one hidden unit and a dense layer that connects the output of the LSTM at the last time step to a single output neuron with linear activation. The LSTM model was implemented using the Keras package in Python, the Adam activation function and the mean squared error as loss function. To predict the discharge of a single time step (day), we provided as input the last t consecutive time steps of independent meteorological variables (daily precipitation [mm.d^{-1}] and air temperature [°C]). We obtained the best hyperparameters of the LSTM model through a trial-and-error tuning approach. We varied the values of the following hyperparameters: length of the input sequence (time-steps), number of neurons in the hidden layer and number of epochs. Our analysis resulted in the selection of 50 neurons, 50 epochs and 365 days as time steps.

HBV model

We benchmarked the performance of the LSTM model against the bucket-type HBV-Light version model (Seibert &Vis, 2012). The HBV model consists of four routines including the snow routine, the soil routine, the groundwater routine, and the routing routine. This model usually simulates daily discharge based on daily precipitation, daily air temperature, and estimates of long-term monthly potential evapotranspiration rates. The HBV was used as both a lower and upper benchmark with two different parameterization methods (Seibert et al., 2018). As a lower benchmark, we used the ensemble mean of simulations with 1,000 randomly selected parameter sets, referred to hereafter as ‘uncalibrated HBV’. For the upper benchmark, we calibrated the HBV model using an automatic genetic algorithm and the Nash-Sutcliff efficiency (NSE) as objective function, referred to hereafter as ‘calibrated HBV’. In both cases, we specified feasible parameter ranges based on previous model applications.

Calibration procedure

The LSTM and HBV were calibrated individually for each one of the catchments resulting in six LSTM models and six HBV models. We calibrated and validated the models according to the Differential Split Sample Test (DSST) proposed by Klemes (1986) for changing conditions. According to Klemes (1986), if the model is intended to simulate streamflow in a wet climate scenario, then it should be calibrated on a dry period of the historical record and validated on a wet period and vice-versa. Additionally, we calibrated and validated a model under constant conditions.

Selection of the calibration and validation periods

The period between 1961 and 2018 was used to select the constant and changing conditions periods. We mimicked the changing conditions by selecting two continuous periods in the time series with different hydrological conditions in the historical record. The dry and wet periods were chosen as the annual discharge below and above the long-term average discharge, respectively. The discharge changes between the periods were on average 50%. This is similar to the future hydrological changes expected for Switzerland of an increase in mean and maximum floods of 5 – 24% in the near future and of 25 – 49% in the far future, with exception to the Southern alpine catchments, where the mean annual floods may decrease in the far future (Köplin et al. (2014). For the constant conditions, we selected continuous periods containing both dry and wet years.

We also selected calibration periods with different time series sizes, ranging from two to six years (2, 3, 4 and 6 years) for each catchment and condition (constant and changing), to test the influence of the amount of data used in the calibration on the model performance. We limited this analysis to six years due to data availability. We needed continuous periods with only low or high discharge, which were limited on average to six years across all the catchments.

Evaluation metrics and robustness

We evaluated model performance using Nash-Sutcliffe Efficiency (NSE) (Nash and Sutcliffe, 1970), Kling-Kupta Efficiency (KGE) (Gupta et al., 2009), Non-Parametric Efficiency (NPE) (Pool et al., 2018) and Mean Absolute Relative Error (MARE) (Staudinger et al., 2011). The metrics range from $-\infty$ to 1, where 1 indicates perfect agreement between simulations and observations, and values lower than zero indicates very poor performance. These metrics were chosen to evaluate different hydrograph phases, the NSE focus on peaks and discharge dynamic, the KGE focus on the mean, variability, and dynamic, the NPE is the non-parametric version of KGE, and finally, the MARE focus on low to medium flows. The robustness was calculated as the difference between the efficiency in calibration and validation (Hallouin et al., 2020). The independent two-sample t-test was used to evaluate whether the LSTM mean robustness was equal to the robustness obtained with the HBV model, and to compare the mean robustness of the LSTM under changing and constant conditions, at the significance level (α) of 0.05.

RESULTS

Model performance

In calibration mode, the LSTM performed better than the HBV model for all criteria as expected, since it is more flexible (it has more degress of freedom) than the conceptual model. However, the performance of the LSTM decreased more than the calibrated HBV when switching to the validation periods (Figure 2). The uncalibrated HBV model performed less well, but the performance was still better than what one might expect from a model run with random parameters and/or no local information. Therefore, we considered that a model performance of about 0.5 for NSE basically indicates that a model has no skill. By definition its performance did not systematically differ between calibration and validation periods for the uncalibrated model. For KGE the patterns were roughly similar, whereas for NPE and MARE, which are more different from the NSE used for calibration, the calibrated models (LSTM and HBV) were less superior compared to the uncalibrated HBV model, especially when using fewer years during calibration.

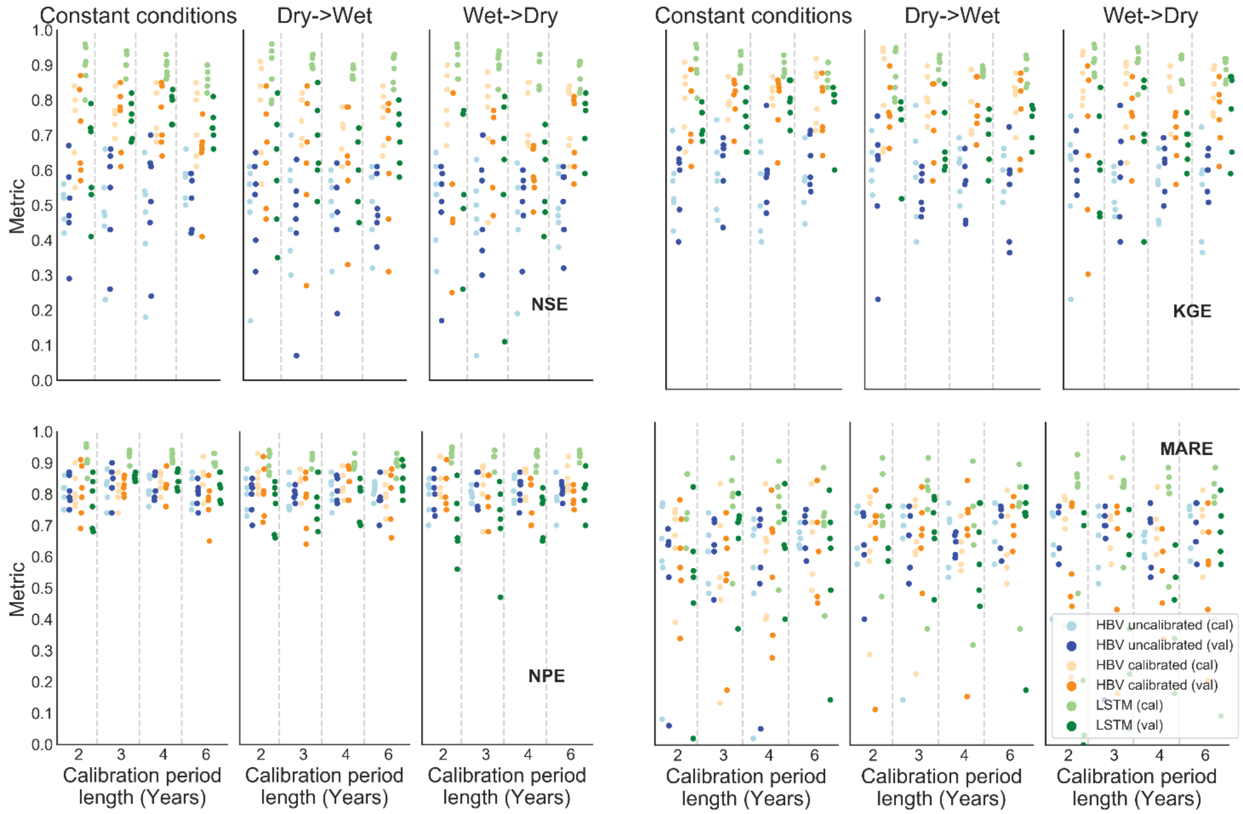


Figure 2. Dot plots of model performance in calibration (cal) and validation (val) periods for the six catchments under study. Each grid is one metric, and within each grid, each subgrid is one condition, from left to the right: Constant conditions, Dry -> Wet (calibration in a dry period and validation in a wet one), and Wet -> Dry (calibration in a wet period and validation in a dry one). The y-axis was limited to the interval between 0 and 1.

The effect of the time series size used in calibration on the performance of the models is represented in the x-axis of Figure 2. There was a positive correlation between the time series length and model performances, which was more pronounced for the LSTM model. When evaluating the model's performance against metrics not used for the optimization of the model (i.e. KGE, NPE and MARE), the increase in the time series length used in calibration is essential to obtain LSTM performances comparable to the HBV model during validation for contrasted conditions. Simulations for changing conditions performed less well than those for constant conditions in validation. However, the differences were less pronounced using the maximum number of years in calibration (i.e., six years).

The hydrographs and scatter plots of observed and estimated discharge using the best configuration, i.e., using six years in calibration, for one of the study catchments are presented in Figure 3 and Figure 4, respectively. The hydrograph shows the underestimation of the peaks, especially those in spring (when the snow accumulated during the winter starts to melt) by all models. However, most low and mid-flows were predicted well. This is clearly shown in the scatter plots of the observed and simulated flows in Figure 4. The scatter plots also indicate that the predictions deviate more from the observed values in the uncalibrated HBV model. There is an underestimation of the peaks when applying the model in conditions wetter than those it was calibrated in, and the LSTM model simulations are slightly less spread than those of the calibrated HBV model.

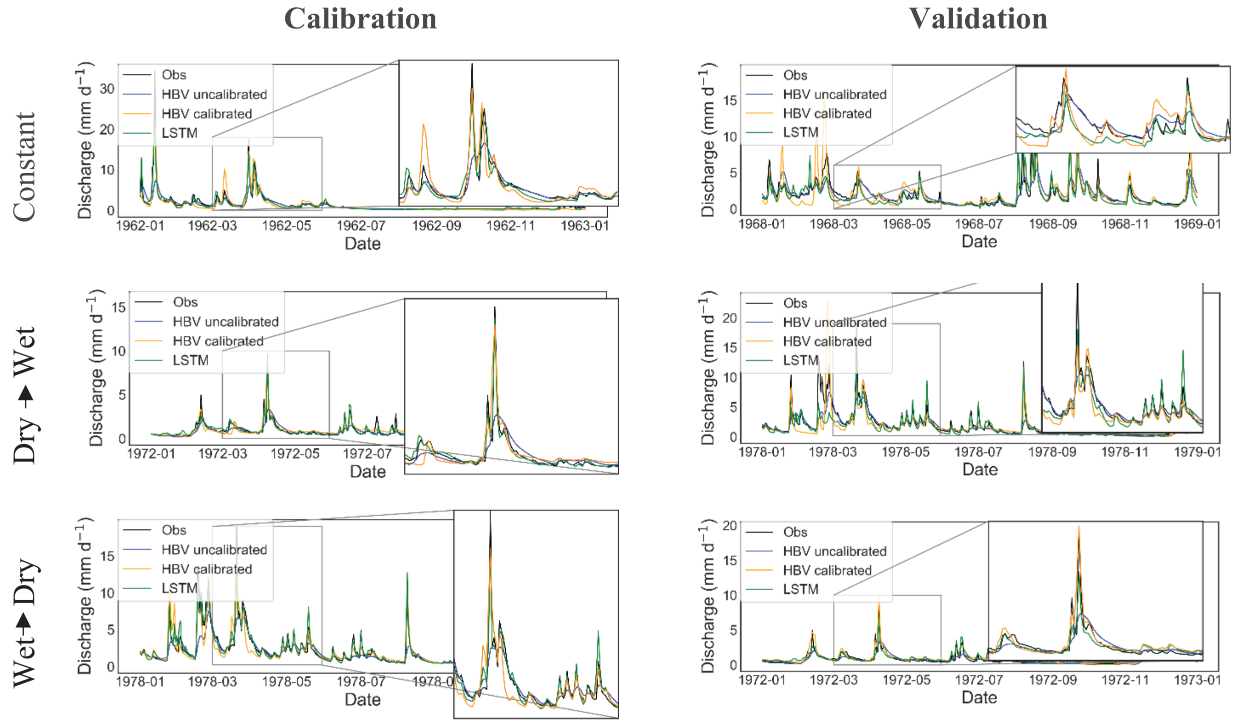
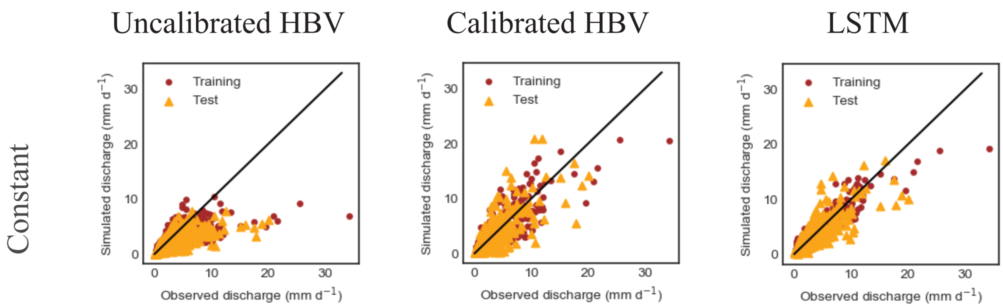


Figure 3. Observed and simulated hydrographs.



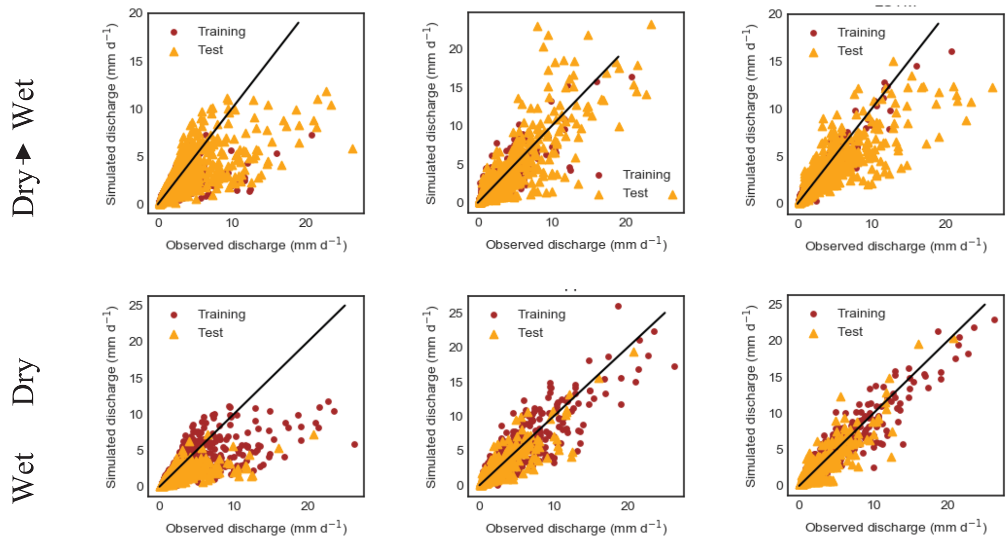


Figure 4. Scatter plot of the observed and the simulated discharge.

Model robustness

The model robustness was evaluated as the difference in performance between calibration and validation periods (Table 2). The LSTM was considered robust enough for generalization in changing conditions when the LSTM mean robustness did not significantly differ from both the mean robustness of the bucket-type model and of the constant period for most of the metrics.

The calibrated HBV was always more robust than the LSTM model for both constant and non-constant conditions. The LSTM was robust enough for changing conditions only when the model was applied in a drier period than that used in calibration and using the maximum number of years during calibration (six years). While a good indication of robustness was already observed with a shorter time series used in the calibration for the HBV, a longer dataset length was needed for the LSTM.

Table 2. Average robustness of the LSTM (left number) and the calibrated HBV model (right number) defined by the subtraction between the efficiency in calibration and validation. Bold values are showed when the LSTM did not differ significantly from the calibrated HBV. Underlined values are showed when the LSTM under a changing condition did not differ significantly from the constant condition (α = 0.05).

Calibration period length (years)	NSE	KGE	NPE	MARE
		Constant		
2	0.28|0.04	**0.16|0.03**	0.14|0.01	0.27|0.06
3	0.16|0.00	0.17|0.00	0.07|-0.01	0.1|-0.02
4	0.12|0.02	**0.09|0.04**	**0.07|0.03**	**0.08|0.04**
6	**0.14|0.10**	**0.10|0.04**	**0.08|0.07**	**0.12|0.07**
		Dry→ Wet		

<table>
<tr><td>2</td><td>0.28|0.13</td><td>0.17|0.04</td><td>0.14|0.04</td><td>0.18|0.00</td></tr>
<tr><td>3</td><td>0.24|0.13</td><td>0.21|0.08</td><td>0.13|0.05</td><td>0.06|-0.06</td></tr>
<tr><td>4</td><td>0.26|0.09</td><td>0.18|0.02</td><td>0.11|-0.01</td><td>0.06|-0.18</td></tr>
<tr><td>6</td><td>0.19|0.15</td><td>0.14|0.04</td><td>0.05|0.00</td><td>0.07|-0.04</td></tr>
<tr><td colspan="5">Wet→ Dry</td></tr>
<tr><td>2</td><td>0.31|0.24</td><td>0.28|0.20</td><td>0.23|0.03</td><td>0.54|0.14</td></tr>
<tr><td>3</td><td>0.31|0.09</td><td>0.21|0.07</td><td>0.21|0.05</td><td>0.34|0.18</td></tr>
<tr><td>4</td><td>0.32|0.18</td><td>0.22|0.14</td><td>0.17|0.07</td><td>0.41|0.20</td></tr>
<tr><td>6</td><td>0.13|0.04</td><td>0.12|0.07</td><td>0.11|0.06</td><td>0.16|0.10</td></tr>
</table>

DISCUSSION

The LSTM had poorer performance under changing conditions. Others have found similar results when applying process-based models under changing conditions (Refsgaard and Knudsen, 1996, Xu, 1999, Seibert, 2003, Wilby, 2005, Chiew et al., 2009, Vaze et al., 2010, Bastola et al., 2011).

Overall, when calibrated, LSTM resulted in a much better fit than HBV. However, the performance drop when going into validation mode is also much larger for LSTM (less robust). For the validation period, LSTM was at best as good as HBV (especially for other criteria than used in calibration and for changing conditions).

The LSTM was shown to be more dependent on dataset length to perform as well as the bucket-type model. The improvement in model performance/robustness with the increase of the time series size used in calibration was also observed by Ayzel & Heistermann (2021) and Gauch et al. (2019) while testing the performance of LSTM networks for streamflow prediction in constant conditions. Here, this positive correlation was more pronounced for the constant conditions than in changing conditions. The lesser contribution of the time series size in model performance under changing conditions may be explained by the limitation of the data provided for the calibration (only dry or wet periods used in calibration), that is, less information about the hydrological processes was provided to the model. The physical constraints of the HBV model made the need for longer data series in calibration less important, indicating the suitability of this model for predictions when data is limited. The same was observed by Ayzel & Heistermann (2021) while comparing a LSTM network to the GR4H conceptual model.

The robustness analysis showed that LSTM is robust enough for climate transposability to a drier period. The generalization from a dry period to a wetter period is less satisfactory, mainly because in this case, the model needs to extrapolate to a discharge range not used in calibration, as also reported by Pan et al. (2019) and Wilby (2005) employing traditional hydrological models.

It is important to highlight that in this model setup the LSTM was trained on individual catchments and its calibration over a large number of catchments and with a larger data series can yield better results and should be explored further. However, comparing models with different structures is not an easy task, especially when trying to keep a fair comparison between the models. More sophisticated hyperparameter tuning techniques may also improve the LSTM model's simulations, as well as coupling the model with process-based models.

CONCLUSION

In this work, we tested the predictive ability of the LSTM for daily discharge prediction in snow-influenced catchments under changing conditions. When calibrated, LSTM resulted in a much better fit than HBV, however, in validation mode, LSTM often performed worse than HBV (especially for other criteria than used in calibration and for changing conditions). The performance drop when going into validation mode was larger for LSTM, indicating less robustness, and the data-driven model was shown to be more dependent on dataset length used in calibration to deliver robustness comparable to a bucket-type model.

Despite this, the results indicate that using longer data series in calibration can benefit the use of LSTM in contrasting conditions. We recommend that other LSTM modelling setups should be studied further to improve the model performance in such conditions.

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6 UNCERTAINTIES OF THE CLIMATE CHANGE IMPACTS ON THE PROJECTED STREAMFLOW - PAPER IV

In this paper, we aim to investigate the individual impact of several sources of uncertainty to the total uncertainty in the projected discharge, and how to combine the results of the ensemble members. The uncertainty sources include two emission scenarios (ES), four global climate models downscaled by one Regional Climate Model (GCM-RCM), two bias correction techniques (BC), and one hydrological model with ten different parameter sets (HMP) and four precipitation data input used in calibration (HMI).

Uncertainties of the climate change impacts on the projection of discharge in South Brazil

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Abstract

The hydrological projections provided by the outputs of the integration of climate models and hydrological models include multi-source uncertainties, which may affect adaptation plans facing climate change. In this paper, we investigated the overall uncertainty in the hydrological impact modelling chain as well as strategies for the ensemble estimate of the changes in the projected discharge of ten catchments in South Brazil. We considered two emission scenarios (ES), four Global Climate Models downscaled by one Regional Climate Model (GCM-RCM), two bias correction (BC) methods, four input data used in the hydrological model calibration (HMI), and ten sets of calibrated hydrological parameters (HMP). The hydrological model was calibrated and validated with good performance indices in the 'present-day' (1990 - 2009) for daily discharge series. The variability of GCM-RCM projections was the most significant uncertainty contributor in the projection of changes in the mean discharge, accounting for 46% and 33% in near and far future, respectively, followed by the input data used in the hydrological model calibration (average of 38% and 32% in near and far future, respectively). Bias correction and emission scenarios contributed relatively little to the total uncertainties, while the hydrological model parameters did not contribute to the uncertainty. The use of a fitness-for-purpose (FFP) weighted ensemble average was shown to minimize the error in the annual maximum discharge, mean daily discharge, and maximum cumulative deficit in 80%, 50% and 50% of the catchments in relation to both the traditional ensemble mean (equal weights) and ensemble median. The FFP weighting strategy seems to be promising in climate change impact assessments on discharge when usually deep uncertainty is a challenge. It delivers tailor-made projections on specific purpose variables considering all the input sources with no increase in computational cost. Therefore, the method can be easily included in uncertainty analysis routines.

Key-words: climate change, fitness-for-purpose model, ensemble strategy, model adequacy

Introduction

A new report, by the Intergovernmental Panel on Climate Change (IPCC) points to a rise in global surface temperature of around 1.5°C as early as 2030, one decade sooner than expected. These changes in the near and distant future, will cause unavoidable increases in the frequency and intensity of hot extremes, marine heatwaves, and heavy precipitation, agricultural and ecological droughts in some regions, and proportion of intense tropical cyclones, as well as reductions in Arctic Sea ice, snow cover and permafrost (IPCC, 2021). Studies investigating the impact of climate change on the hydrological response have grown substantially in the last two decades worldwide. Globally, climate change is projected to reduce terrestrial water storage in many regions, especially those in the Southern Hemisphere. Increase in the water availability is projected in eastern Africa, south Asia and northern high latitudes, especially northern Asia (Pokhrel et al., 2021). In South America, major decreases are projected in the annual mean discharge, except for the Uruguay basin where a positive trend is expected (Brêda et al., 2020).

In Brazil, local-scale studies investigating the climate change impacts on water resources are rather inconclusive mainly due to the quality and consistency of the results. According to Borges de Amorim and Chaffe (2019) criteria on evaluating climate change studies, the quality of the study considers uncertainty sampling, and the consistency is the agreement on the change signal among several models of diverse structures. In South Brazil, region that encompasses three main basins: Uruguay, South Atlantic and Parana, were found 23 studies on the YARA web-based tool (Borges de Amorim, Silva de Souza & Chaffe, 2020, Borges de Amorim & Chaffe, 2019) investigating the impacts of the climate change on the discharge (mainly located in Parana basin), however the lack of a multi-model ensemble analysis makes it difficult to draw some consistent conclusions about the climate change impacts. In Uruguay basin, changes in minimum and mean discharge were inconclusive (Rosenzweig et al. 2004, Fill et al. 2013, Adam & Collischonn, 2013, Oliveira et al. 2015, Ribeiro Neto et al., 2016, Queiroz et al. 2016, Zaninelli et al. 2018), while an increase in maximum discharge is projected with low quality and consistency (Rosenzweig et al. 2004, Oliveira et al. 2015, Ribeiro Neto et al. 2016). In the South Atlantic basin, changes in the minimum discharge are inconclusive (Ribeiro Neto et al., 2016), and increases are projected in mean (Queiroz et al., 2016, Ribeiro Neto et al., 2016, Tejadas et al., 2016, Zaninelli et al, 2018) and maximum discharge (Ribeiro Neto et al., 2016), however with low consistency and quality. In the Parana region, decreases are projected in minimum (low to medium quality), mean (inconclusive) and maximum discharge (low quality and consistency).

Rainfall-runoff models combined with emission scenarios from global and regional climate models are widely used to assess the future climate change impacts on the catchment scale. Nevertheless, there are large uncertainties in the modelling framework. Modelling is an attempt to represent reality with the aim of understanding a system for supporting decision-making processes. The more complex a geographical system is, the more difficult it is to model. Errors and uncertainties are inherent issues that must be faced in order to assess quality or efficacy of the conclusions (Mark et al., 2015). The current approach used to project the climate change impacts on discharge contain uncertainties mainly related to climate model, downscaling method, bias correction technique, emission scenario, and hydrological modelling. Several authors have studied the relative importance of each source to the total uncertainty. However, the results are still controversial. Despite some authors concluded that the global climate model is the most contributor to the total uncertainty (Wilby, 2006, Prudhomme et al., 2009a, Prudhomme et al., 2009b, Kay et al., 2009, Arnell et al., 2011, Vetter et al., 2017, Krysanova et al., 2017), the hydrological modelling structure and parameter uncertainty cannot be neglected (Bastola 2011, Bosshard et al., 2013, Zhang et al., 2014, Goderniaux et al., 2015, Dams et al., 2015, Eisner et al., 2017, Samaniego et al., 2017, Troin et al., 2018, Anaraki et al., 2021, Ju et al., 2021). In addition, despite of the importance of the data input to hydrological modelling on the uncertainty of model simulations (Meresa et al., 2021, Pokorny et al., 2021), to the best of our knowledge, the study of the data input in the total uncertainty is rare in climate change impact assessments, with exception for the recent work of Tarek, Brissette and Arsenault (2021).

One of the ways of addressing some of these uncertainties is through ensemble modelling. An ensemble involves the use of multiple diverse models to predict an outcome, with the objective of reducing the errors resulting from only one deterministic model. Ensemble modelling has often been used in the climate and atmospheric sciences, where operational ensembles have been in use for well over a decade. The simple averaging of the ensemble (equal weights) tends to outperform individual models, and the use of the ensemble median can handle outliers (Georgakakos et al., 2004, Her et al., 2019). Likewise, weighted ensemble strategies, in which different weights are assigned to individual model ensemble members based on model's accuracy is shown to be a good predictive choice (Chen et al., 2017). However, the weighting system of these approaches usually relies on the reliability of the climate model in predicting climatic variables, rather than focusing on the purpose variable, such as discharge (Weiland et al., 2012). Dong et al (2021) used a flow-based ensemble strategy to assign probabilistic weights to individual GCMs based on the likelihood of each model to be a correct representation of the hydrological system, given the daily flow time-series, however it still lacks including other uncertainty sources in the weighting system.

In numerical weather and hydrological forecasts applications, the use of probabilistic ensemble is well established and thoroughly evaluated (Stephens, Edwards & Demeritt, 2012, Fan et al., 2015). However, in climate change impact assessments, an open scientific question is how to better combine the ensemble simulations of several models in order to deliver better simulations to be used by decision makers. In addition, the reliability of the optimized weights in delivering good simulations for different aspects of the hydrological response is rarely tested. In this study we analysed the uncertainties in the climate change projections on discharge considering two emission scenarios, four Global Climate Models downscaled by one Regional Climate Model (GCMs-RCM), two bias correction methods, ten hydrological parameter sets and four input data sources in the calibration of the hydrological model. We aimed to investigate the uncertainties inherent to the assessment of the climate change impact on the hydrological response, opportunities, and limitations. The results presented here confirm some well-known findings in the literature, as well as provide new insights that can be useful for modellers, and water resources managers aiming to apply climate change assessments with focus on discharge.

Study area and Data

The study area consisted of ten catchments in South Brazil (Figure 1). The South region is economically very important, as it has the second highest per capita income in the country, high human development indices, and it is responsible for 17% of the national Gross Domestic Product (GDP) (IBGE, 2018). This region is composed of three important hydrographic regions, the Parana (PRN), South Atlantic (SOA) and Uruguay (URU) basins. The PRN region has the greatest economic development of Brazil and is strongly dependent on energy supply from hydropower plants. The SOA is noteworthy for its significant population contingent, for economic development and for its importance for tourism, and the URU has great importance for the country due to its agroindustry and hydropower potential.

The study cases were randomly selected using the catchments available in the CAMELS-BR dataset (Chagas et al., 2020). The area of the study regions ranged from 376 km^2 to 123’233 km^2, and the altitude ranged between 232 m and 802 m (Table S1 in Appendix C).

The climate is predominantly temperate, with the lowest winter temperatures in the country, the average annual precipitation varies from 1’250 to 2’000 mm and it is well distributed throughout the year.

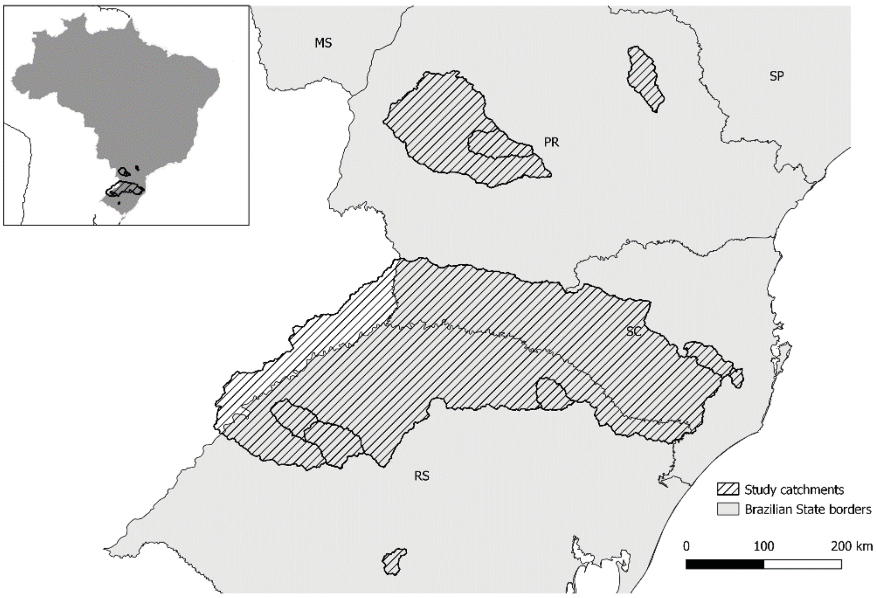


Figure 1. Study catchments.

Data

Present time

Meteorological daily time series data were needed to calibrate the hydrological model. These included precipitation from MSWEP v2.2 (resolution of 0.1°, Beck et al., 2019), Hidroweb (Brazilian National Water Agency), CFSv2 (resolution of 0.2°, Saha et al., 2011) and ECMWF (resolution of

0.1°, Muñoz Sabater, 2019); potential evapotranspiration from GLEAM v3.3a (resolution of 0.25°, Miralles et al., 2011; Martens et al., 2017); and average temperature from CPC (resolution of 0.5°, NOAA, 2019). MSWEP v2.2, CPC, GLEAM v3.3a and discharge data were obtained directly from the CAMELS-BR dataset (Chagas et al., 2020). CFSv2 and ECMWF data were retrieved from Google Earth Engine. The temperature and precipitation over the catchment were estimated by the average grid value, except for the Hidroweb point data, where the Thiessen method was used.

Future periods

The future scenarios of climate change were obtained from four global climate models downscaled by the Eta regional climate model of the National Institute for Space Research (INPE). The description of the GCMs is presented in Table 1. The climate models were forced by two emission scenarios, the Representative Concentration Pathway RCP 4.5 and RCP 8.5.

Table 1. Global climate model description.

GCM	Full name of GCM	Institution
HadGEM2-ES	Hadley Centre Global Environmental Model version 2 – Earth System	Hadley Centre
MIROC5	Model for Interdisciplinary Research on Climate version 5	Atmosphere and Ocean Research Institute, University of Tokyo, National Institute for Environmental Studies and Japan Agency for Marine-Earth Science and Technology.
CanESM2	Canadian Earth System Model version 2	Canadian Centre for Climate Modelling and Analysis (CCCMA)
BESM - OA 2.5.1	Brazilian Earth System Model	National Institute of Space Research (INPE)

The Eta regional climate model simulations were obtained from <https://projeta.cptec.inpe.br>. Data downloaded in July 2020.

Methods

Bias Correction

The climate simulations provided by the GCMs-RCM models were post-processed using two bias correction methods to adjust the simulated data to the observed climatology. In this work, we applied the Linear Scaling (Lenderink, Buishand and Deursen, 2007) and the Empirical Quantile Mapping (Amengual et al., 2012), using a monthly correction factor.

Hydrological modelling

The bucket-type HBV-Light version model (Seibert and Vis, 2012), referred to hereafter as HBV was used in the hydrological modelling. The HBV model is considered a semi-distributed model since it allows for the catchment to be sub-compartmentalized into different elevation zones, derived from a digital elevation model. As input, HBV requires temperature, precipitation, and long-term potential evapotranspiration rates.

The HBV model was used in this study under two different types, (i) Standard, consisting of four routines, the snow routine (neglected in this study as the catchments under analysis do not have significant snow), the soil routine, the groundwater routine, and the routing routine, and (ii) Simplified Soil Routine, where instead of the usual three soil routine parameters (FC, LP and BETA), it had a single soil parameter (Recharge Fraction), which is a value between 0 and 1, and specifies the fraction of water entering the soil that is going to recharge. We ran the HBV model for both routines in each one of the ten catchments and selected the best individual routine.

Calibration and validation of HBV

The modelling period was the years between 1990 and 2009, available in the CAMELS-BR dataset, in which there is the largest number of discharge gauge stations with available data in Brazil. The model was calibrated in 1990 – 2004, with one year of warming-up, and validated in 2005 – 2009.

The Non-Parametric Efficiency (N_{PE}) (Pool et al., 2018) was used as the objective function to calibrate HBV. The HBV was run with 10 different parameter sets to address the uncertainties in modelling parameterization. HBV was calibrated using a genetic algorithm and Powell (GAP) method. The GAP optimization method works by selecting and recombining high-performing parameter sets with each other. At the conclusion of these runs, the parameter set associated with the highest objective value was selected. This process was repeated 10 times to produce 10 optimized parameter sets.

Evaluation metrics

We applied the statistical metrics Nash-Sutcliffe Efficiency (N_{SE}) (Nash and Sutcliffe, 1970), Kling-Kupta Efficiency (K_{GE}) (Gupta et al., 2009) and Non-Parametric Efficiency (N_{PE}) (Pool, Vis and Seibert, 2018) to evaluate the model performance. These metrics were chosen to evaluate different hydrograph phases, the N_{SE} focus on peaks and discharge dynamics, the K_{GE} focus on the mean, variability, and dynamic, and the N_{PE} is the non-parametric version of K_{GE}.

Climate change impacts on the discharge

The climate change scenarios were projected on the hydrological components by using the corrected simulated climate variables as input to the calibrated hydrological models. The projected discharge under the two emission scenarios were compared to the simulated discharge in a reference period (1991 to 2009) to compute the changes projected for the future (near: 2040 – 2069 and far: 2070 – 2099). The changes were computed using a simulated reference period in order to avoid that errors in the hydrological modelling were identified as changes.

Uncertainty analysis

The predictive uncertainties reflected five main sources of uncertainty: emission scenario (ES), global climate model downscaled by one regional climate model (GCM-RCM), bias correction (BC), hydrological model parameters (HMP) and hydrological model data inputs (precipitation) (HMI). We computed the relative contribution of each source of uncertainty to the change in mean discharge using the analysis of variance (ANOVA, Hawkins and Sutton, 2009).

Fitness-For-Purpose (FFP) weighting system

The optimization of the ensemble weights by the Nelder-Mead (Gao and Han, 2012) algorithm was performed to investigate whether the use of a Fitness-For-Purpose (FFP) weighting system, in which the optimization of the ensemble weights is based on the purpose variable, improved the predictive ensemble ability in relation to a simple ensemble average (equal weights) and ensemble median. In this method, not only the climate models were weighted based on accuracy but each individual ensemble member representing the combination of all the uncertainty sources under analysis and its interactions. The t-test for mean comparison was used to determine whether the means of the different ensemble strategies were equal at the significance level (α) of 0.05. The step-by-step approach is described as follows:

1. Optimize the ensemble weights using the observed and simulated purpose variable in a historical period (e.g.: Nelder-Mead optimization algorithm). The loss-function was the absolute relative error (Equation 1):

$$Loss\ function = \left|\frac{(\text{observed} - \text{predicted})}{\text{predicted}}\right| \tag{1}$$

2. Validate the optimized weights assigned a hold-out period (test)
3. Use the optimized ensemble weights to project the change in the purpose-variable in future series
4. Check the consistency of the changes

- If less than 60% of the ensemble members agree in the signal of the change: Low consistency
- If 60 – 85% of the ensemble members project the same change signal: Medium consistency
- If more than 85% of the ensemble members agree in the signal of the change: High consistency

Experimental design

Overall, we combined two emission scenarios (ES), four global climate models downscaled by one regional climate model (GCM–RCM), two bias correction (BC) methods, four input data for the hydrological model (HMI) calibration, and one hydrological model run with 10 parameter sets (HMP). In a factorial way, we analysed 640 discharge simulations per catchment.

We evaluated the following discharge flows: long-term mean daily discharge (Q_{mean}) in mm.day^{-1}, long-term annual maximum discharge (A_{max}) in mm.day^{-1}, and monthly maximum cumulative deficit (M_{CD}) (mm.month^{-1}). The M_{CD} statistic was calculated to regularize 60% of the long-term monthly discharge (Equation 2) (Detzel et al., 2016).

$$D_t = \begin{cases} D_{t-1} - Q_t + \delta\hat{\mu}_Q, \text{ if positive} \\ 0, \text{ otherwise} \end{cases} \tag{2}$$

$$M_{CD} = \max(D_t)$$

Where Q_t is the monthly discharge in time t, δ is the discharge regularization, $\hat{\mu}_Q$ is the long-term monthly discharge, and M_{CD} is the maximum cumulative deficit.

Results

HBV model performance and uncertainties

The hydrological modelling uncertainties were addressed regarding the precipitation input data used in the calibration process and the parameters. The HBV model was calibrated and validated with good performance indices (Calibration: $0.5 < N_{PE} < 0.9$, mean of 0.7; Validation: $0.3 < N_{PE} < 0.9$, mean of 0.7). The global model efficiency is shown in Figure 2.

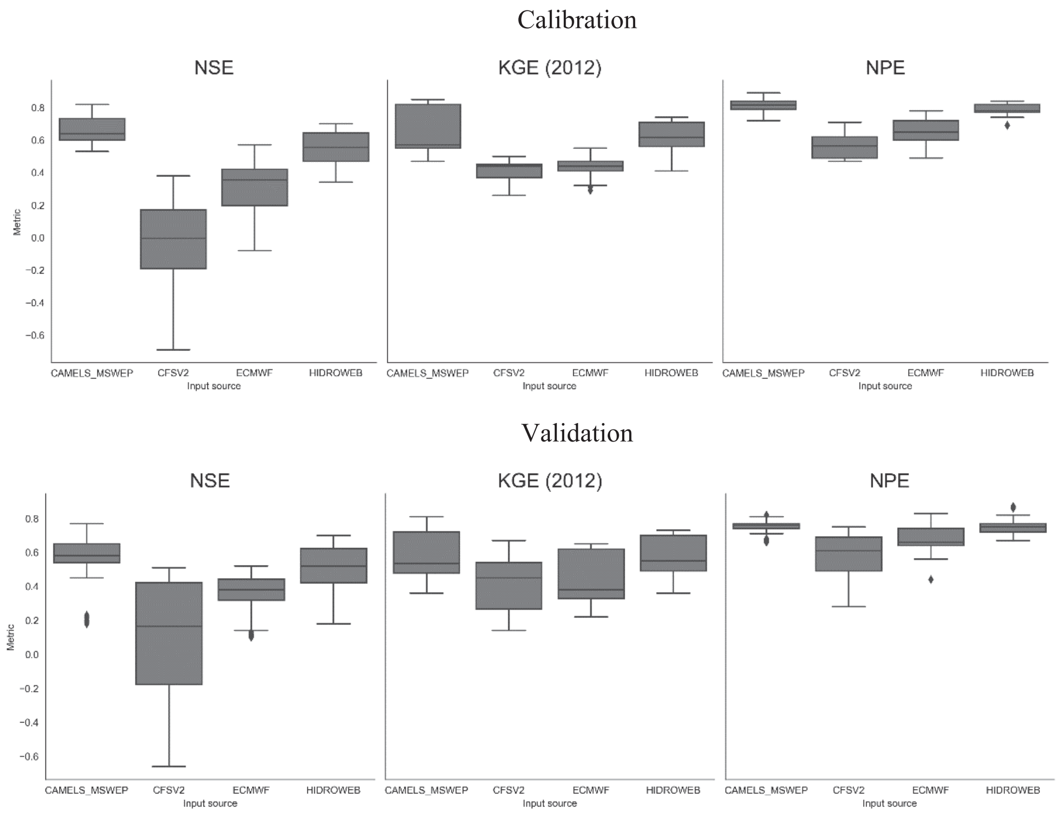
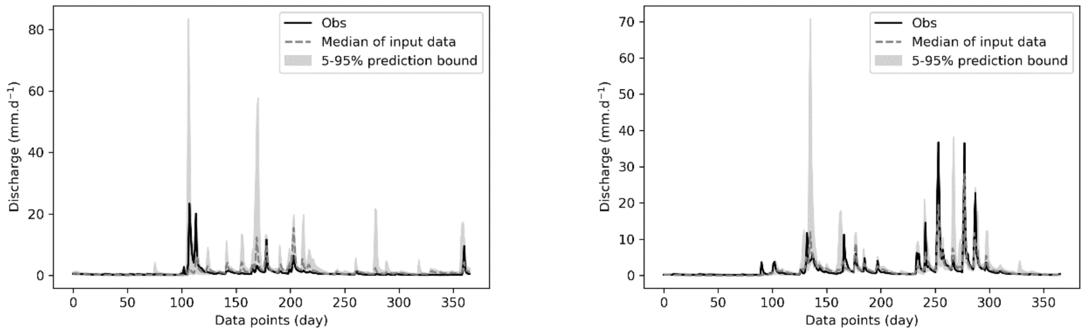


Figure 2. Global performance of the hydrological model for ten catchments in calibration and validation based on different performance metrics (columns), using different input data in model calibration (x-axis). The boxplots show the 10 sets of hydrological parameters simulations per catchment.

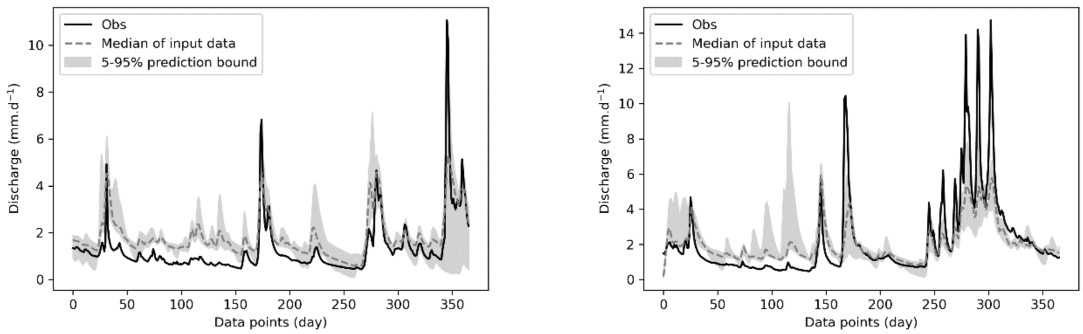
When the hydrological model was tested against other performance metrics not used as objective functions, poor performance was found for the N_{SE} using the CFSv2 as input data, indicating poor representation of peak flows, focus of the N_{SE} metric. Satisfactory performance was obtained for K_{GE}, which is very similar to the metric used in the calibration process, only differing in terms of considering parametric statistics instead of the non-parametric approach. Figure 2 show similar performance results of the hydrological model obtained from the calibration using the MSWEP input data and ground-level gauge stations (Hidroweb), indicating that good quality model-based reanalysis data products are valuable for climate change impact assessments, especially on data-scarce areas.

The best model performance was found for the catchment 85623000 in the Atlantic South basin using the MSWEP (calibration) and Hidroweb (validation) input data. The worst calibration and validation performance were found for the catchment 64830000 in the Parana basin using the CFSv2 data input. The best and worst calibrated catchments will be used as catchment examples in the figures of hydrological model performance in this paper. The hydrographs of simulated and observed discharge for the best and the worst catchments are presented in Figure 3a and Figure 3b, respectively.

Calibration Validation



a



b

Figure 3. Hydrographs of observed and simulated discharge in calibration and validation for (a) São Sepé - Montante catchment (code: 85623000) and (b) Balsa Santa Maria catchments (code: 64830000). The predictive uncertainty bound was computed as the 5% and 95% percentiles of the projections.

There was an overestimation of the discharge for Balsa Santa Maria catchment for the low flows by all the input data, which indicates the poor performance of the model is more related to the structure and/or parameter sets of the model in representing such catchment than quality of the input data used in calibration. On the other hand, an overestimation of the peak flows was found for the São Sepé – Montante catchment.

Figure 4 illustrates the performance of the hydrological model in the representation of the seasonal discharge, A_{max} and water deficits (observed against simulated). As expected, there was a decrease in model representativeness when applying the calibrated model in the daily series to simulate maximum flows and water deficit in the worst catchment. The seasonal discharge was overestimated in the best catchment in Calibration and underestimated in the first half of the annual cycle in Validation. High biases were found using the CFSv2 data product in the simulation of the annual cycle in the worst catchment. However, the CFSv2 input was shown to be more adequate to represent the maximum flows in the worst catchment, and despite of overestimating the water deficits, it could be a better estimate compared to the other input sources that usually underestimate the variable. While the hydrological parameterization seems to not add much uncertainty (shading), the use of different data input in calibration led to a more spread simulation (coloured lines), especially the CFSv2 stood out from the other data inputs.

Calibration — Validation

85623000 — 64830000 — 85623000 — 64830000

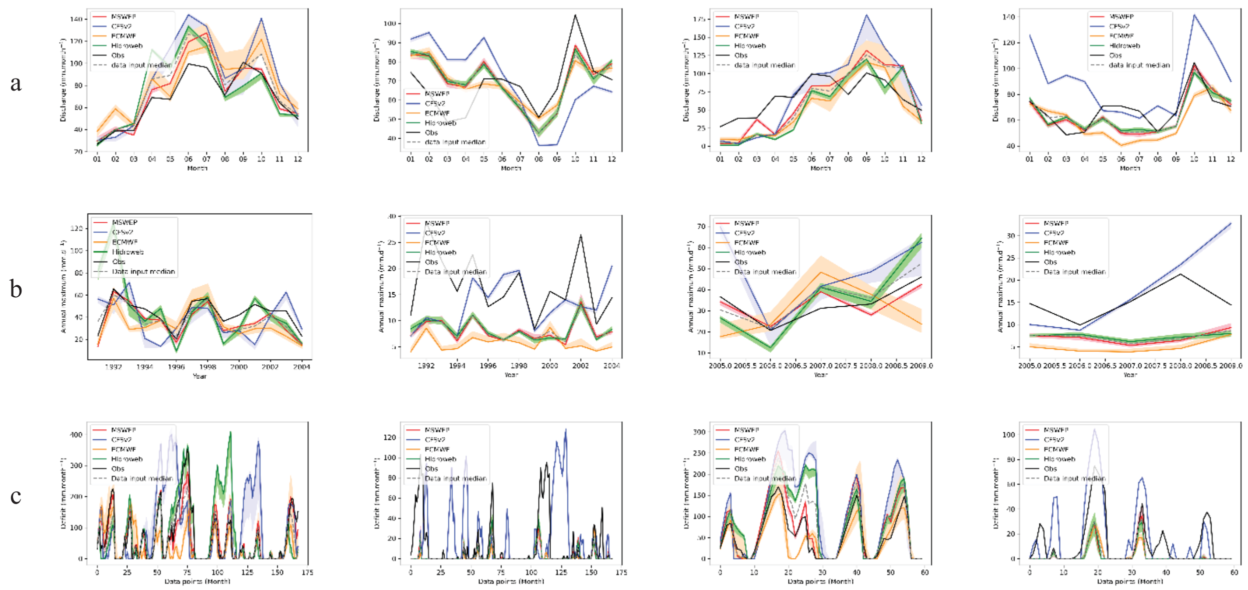


Figure 4. Observed and simulated hydrological variables: (a) long-term seasonal discharge, (b) annual maximum discharge and (c) monthly water deficit in Calibration and Validation for two example study cases (best performance catchment: 85623000 and worse performance catchment: 64830000).

Performance of Bias Correction

The performance of the LS and EQM bias correction of the precipitation outputs of the GCM-RCM were tested by Moura et al (2021). Here, we applied a process-based method for evaluating the impact of the bias correction in the hydrological response as described by Hakala et al. (2018). The bias correction effect was evaluated comparing the discharge simulations using the raw climate model simulations and the bias-corrected simulations. Figure 5 shows the effect of the bias correction in the air temperature, precipitation, and discharge for two example catchments.

Most of the regional climate models underestimated air temperature, except for the Eta-BESM model. The raw simulations of the Eta-HadGEM2-ES and Eta-CanESM2 agreed more to the observed temperature. All the models presented high precipitation biases, and the bias correction showed improvement in the representation of seasonal precipitation, with better performance of the EQM method for precipitation, and LS method for precipitation and discharge. However, Moura et al., (2021) showed that the quantile-based correction factor might represent better other aspects of the precipitation like multi-day and seasonal precipitations not showed in Figure 5.

85623000 64800000

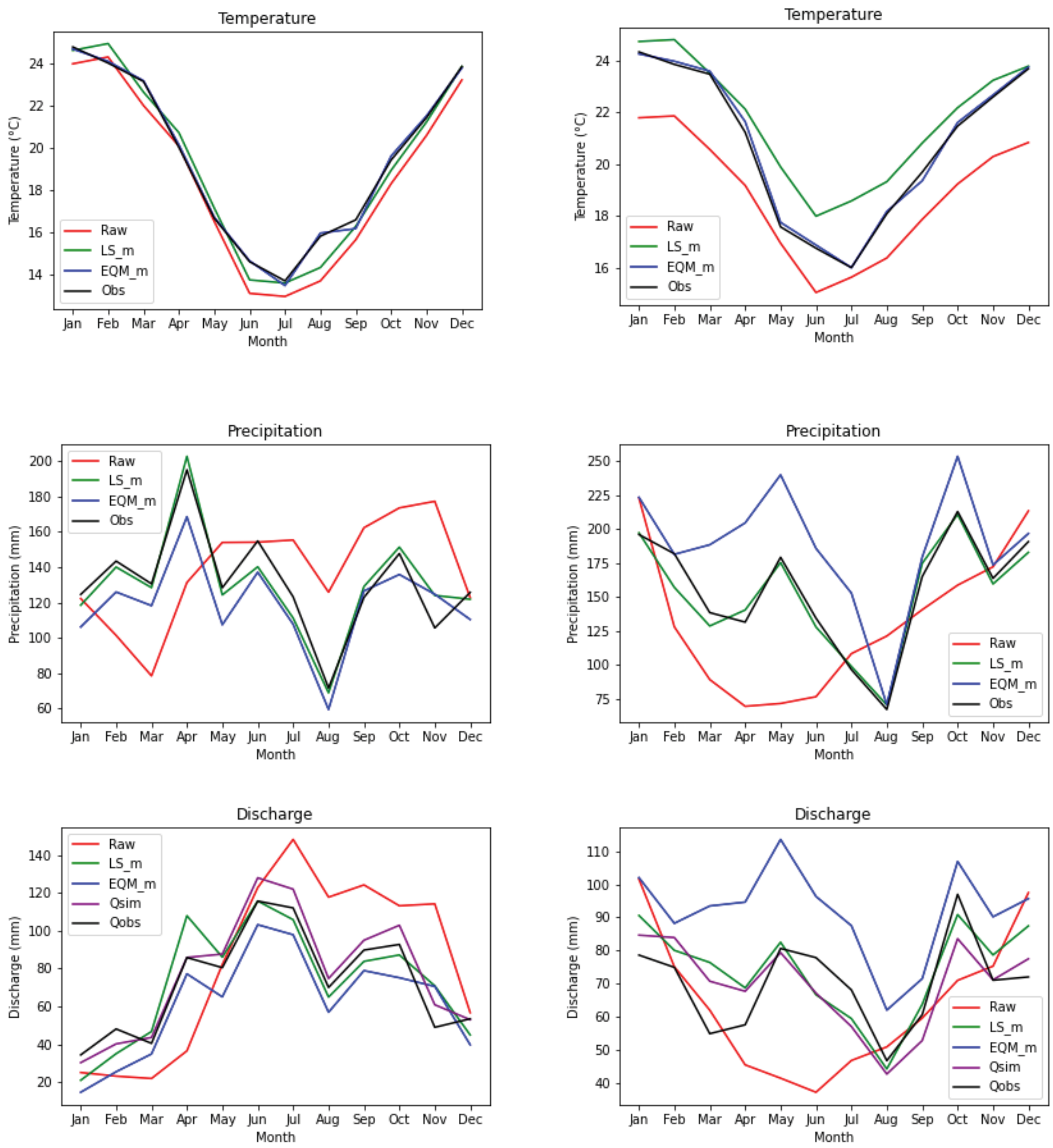


Figure 5. The long-term mean monthly air temperature, precipitation, and discharge for two example catchments. The data from one GCM-RCM are used for each catchment. (left) 85623000, Eta-HadGEM2-ES; and (right) 6480000 catchment, Eta-MIROC5. All figures are for the period 1991-2005. Note the different y-axes for the different plots.

Uncertainty analysis

The results of the ANOVA showed that climate models were the dominant source of uncertainty (average of 46% (near) and 33%, (far)), followed by the input data (average of 38% (near) and 32% (far)), whereas bias correction and emission scenario contributed a relatively small amount of uncertainty to the hydrological projections (4.9% and 3.1%, respectively for near future, and 3.1% and 5.4% for far future) (Figure 6). The parameterization of the HBV model was found to not contribute to the total uncertainty. In far future, uncertainties due to residuals and interactions among sources are larger than in the near future, accounting for 15% and 11%, respectively against 1% and 6% respectively in near future.

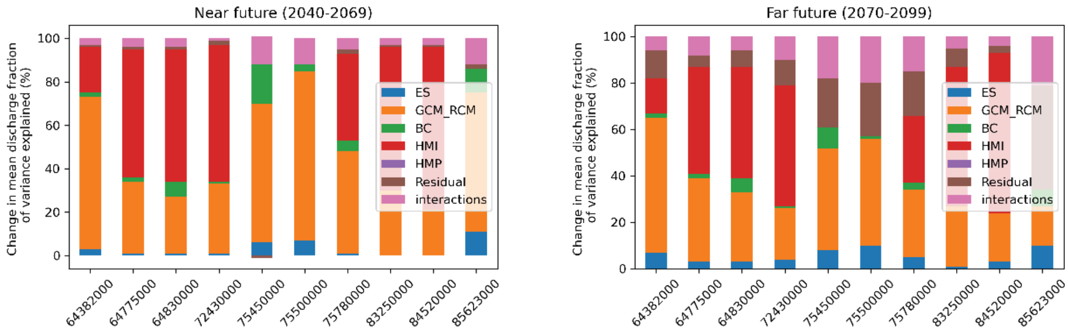


Figure 6. Decomposition of the projection variance. ANOVA partitioning among the five sources of uncertainty (ES: emission scenario, GCM-RCM: Global Climate Model-Regional Climate Model, BC: Bias Correction, HMI: Hydrological Model Input data, HMP: Hydrological Model Parameter), interactions among main sources, and the residual errors for discharge change. Catchments are shown in the x axis.

Ensemble strategy

Tables S2 - S7 in Appendix C show the results of the ensemble simulation in different ways (minimum ensemble member performance, maximum ensemble member performance, ensemble mean, ensemble median and a fitness-for-purpose (FFP) weighting system) for the Q_{mean}, A_{max} and M_{CD} in calibration and validation period. As for the bias correction method, we assumed that the weights optimized in the historical period were valid for a period in the future, considering only the accuracy of the ensemble members in the historical period.

The use of FFP weighted ensemble average was shown to minimize the error in the annual maximum discharge, mean daily discharge, and maximum cumulative deficit in 80%, 50% and 50% of the catchments in relation to both the traditional ensemble mean (equal weights) and ensemble median.

The weights were optimized by purpose variable and cross-validated among the variables in order to test the hypothesis that a fit-to-purpose weighting system is beneficial for climate change assessment in different aspects of the flow (mean, maximum and minimum). The t-test showed that the error is minimized using the fit-to-purpose weighing system in relation to a generalist weighting system (e.g., optimizing the weights for the daily series and applying in maximum flows and vice-versa) ($\alpha = 0.05$). The generalist weighting system was comparable to using the mean or median of the ensemble.

Climate change impacts on the future discharge

The climate change impacts on the purpose variables were estimated by the median of the ensemble projections, and by the FFP ensemble weights in order to visualise the differences among the ensemble strategies (Figure 7). The consistency of the simulations was evaluated based on the agreement of the signal of the change by the ensemble members.

The long-term daily mean discharge was projected to increase in all catchments with medium and high consistency under the RCP4.5 scenario in near and far future, except for the 75780000 where the change was inconsistent. The magnitude of the changes differs depending on the ensemble strategy. Under the RCP8.5 scenario in near future, the ensemble median projects increase for most of the catchments, except for the 643820000 and 64775000 catchments (inconsistent change). However, the FFP projects decreases for 64830000, 75450000, 75500000 catchments. In the far future, decreases are projected with median consistency for the catchments 64382000 and 64775000. On the other hand, an increase is projected for the 64775000 by the ensemble median in agreement with the consistent change among the models.

The A_{max} changes are highly consistent towards an increase in near and far future for both RCP4.5 and RCP8.5 scenarios among the ensemble members for most of the catchments, except for 75450000 and 75550000 in Uruguay basins where a decrease is projected. The changes projected by the FFP estimates are much higher than the ones projected by the ensemble median, and sometimes differ in terms of signal. The scenarios RCP4.5 and RCP 8.5 and the near and far future projections are very similar.

The M_{CD} projections overall indicate a homogeneous increase in drier periods in the near and far future both using the ensemble median and the FFP with high consistency for all the catchments and emission scenarios, except for two catchments in the Uruguay basin (75450000 and 75550000). The magnitude of the changes is much higher using the FFP ensemble estimate.

There was sometimes disagreement between the general trend of the change signal among the ensembles and the signal of change obtained by the ensemble estimate (median or FFP). In the FFP method, that can be related to the optimized weights based on the ensemble accuracy in the historical period. On the other hand, the difference in the median might be related to the interdependency among the ensemble members.

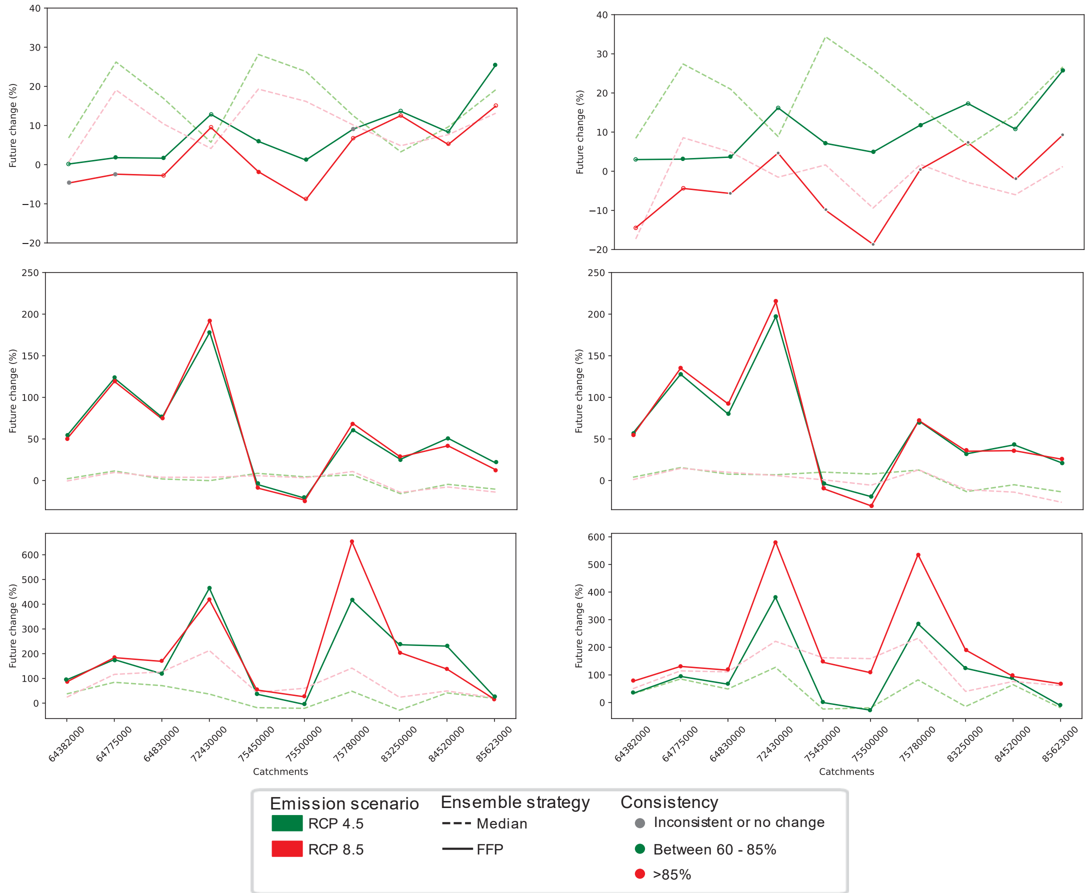


Figure 7. Future changes in (a) long-term mean discharge, (b) long-term annual maximum discharge and (c) long-term maximum cumulative deficit for the near (2040 - 2069) and far (2070-2099) future.

Discussion

The use of different precipitation data input in the hydrological model calibration indicated that the choice of the 'observational data' affected model performance. On the other hand, the results showed that good quality model-based reanalysis data products (MSWEP) are comparable to ground-level gauge stations data (Hidroweb) and could be useful in climate change impact studies where data scarcity is a problem. This confirms the work by Sivasubramaniam et al. (2020), where model-based, gauge and observational gridded data were compared for long-term operational hydropower production planning.

CFSv2 input data was shown to stood out among the data products, and to not lead to good performance of the daily discharge series, but sometimes useful in representing extreme flows. The use of a calibrated hydrological model for the representation of other aspects of the flow not objective of the calibration raised the question about the 'right model for the right reasons' (Kirchner, 2006). In this work, instead of seeking the 'perfect model', we approached the adequacy-for-purpose view, where models should be assessed with respect to their adequacy or fitness for particular purposes (Parker, 2020).

There were some poor performances of the HBV model in some catchments, regardless the data input, which points to either problems in the model structure to represent the hydrological system, or in the parameter ranges used in the model automatic calibration. Despite of the intensive use of the HBV model in European countries, and more recently USA, its use in South America is less investigated. Here, we argue that investigating the model structures uncertainty by including more diverse hydrological models is recommended in future research to compose the ensemble (Dion, Martel and Arsenault, 2021), which was out of the scope of this work.

The comparison of the simulated discharge using the raw simulations from the climate models against the simulated discharge of the model in a reference period (only taking into account hydrological model errors), showed that the bias correction of the climate variables was essential to a better representation of the seasonal discharge.

The uncertainty analysis confirmed previous works showing the high uncertainties due to the climate models in the projection of future discharge (Vetter et al., 2017, Krysanova et al., 2017). The precipitation input data used in model calibration (less investigated in literature) surprisingly showed to be an important factor in the uncertainties, in the same magnitude of climate models, as reported by Tarek, Brissette, and Arsenault (2021), and should not be neglected in uncertainty analysis sampling. Bias correction and emission scenarios were the least contributors to the total uncertainty. The controversial contribution of hydrological model parameters was found to be irrelevant in the uncertainty analysis unlike other studies (Goderniaux et al., 2015, Dams et al., 2015, Zhang, Xu and Fu, 2014, Bastola et al., 2011). In the far future period, the residual errors, and interactions among sources of uncertainties are likely to lead to more uncertain climate projections than in near future.

A fitness-for-purpose optimization of the ensemble weights against the simple ensemble mean or median was shown to improve the representation of other variables than the daily time series. The use of the optimized ensemble weights can take advantage of other sources of uncertainty that can contribute to the total uncertainty, and the interaction between the ensemble models. For example, if there was a model in the performance validation that poorly represented daily flows, removing this model in the early steps of the modelling chain design can hinder the opportunity of using this model to predict well a specific purpose variable for the future (e.g. maximum or minimum flows). In climate change impact assessment chains, a fitness -for-purpose model seems to be more important than the right model for the right reasons when deep uncertainties exist.

Limitations of the study

Recent studies have shown that the use of a single hydrological model tend to under-sample the variability needed to provide a good representation of streamflow observations. A multi-hydrological model approach is recommended in further studies.

In reference to the proposed fitness-for-purpose weighting system, many questions are still open regarding this approach and should be further studied, such as the validation of this method in more catchments, and with diverse hydrological characteristics. The consequences of the interdependence among the ensemble members on finding the optimal weighting system was also not the scope of this paper. Additionally, considering that the 'true value' or observed value used for minimizing the loss function is only one realization of a stochastic process like discharge, the use of the optimized values in the historical might lead to a false idea of optimal performance, and even aggregate more uncertainties to the climate change assessment cascade, especially when applying these weights in long-term projections. Before applying this method in practical exercises with end-users, we recommend additional analysis for the validation of this approach.

Conclusion

The uncertainties in the projection of discharge can be very large, pointing to the importance of the deep investigation of the uncertainty in the climate change impact assessment on water resources. The climate models were confirmed to yield large uncertainties to the total uncertainty (as expected), and the quality of the precipitation input data was surprisingly in the same magnitude of climate models. The bias correction and emission scenarios were found to be the least contributors to the total uncertainty. The hydrological model parameters did not contribute to the uncertainty.

At the end of the day, a large ensemble is challenging to work with due to the size and complexity. The urge to process and combine this huge amount of data generated in one value (median, mean) is very appealing. However, here we aimed to demonstrate that instead of looking for a perfect model (right for the right reasons), more importantly is working with a fit-to-purpose model, and for that, the individual members of the ensemble should not be combined in a single estimate in the first steps of the modelling cascade. The use of optimized weights by purpose variable can help representing aspects of the flow not used in the hydrological model calibration process.

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7 CONCLUSIONS

The results presented in this thesis confirmed the hypothesis that the uncertainties can significantly influence the magnitude of the climate change impacts projected on river discharge. The climate models yield great uncertainties to the total uncertainty (as expected), the bias correction was shown to be a great contributor as well as the data input used in the hydrological model calibration process. The hydrological model parameters did not contribute to the uncertainties in the climate change assessment cascade.

The use of a data-driven method as a hydrological model was tested under changing conditions, and despite of the general good performance of the model (comparable to the HBV bucket-type model), the LSTM network was less robust under changing conditions; especially extrapolating the trained parameters to a condition wetter than the one used in calibration. Because of that, the use of data-driven methods are not recommended in climate change assessments (where climate and hydrological patterns are expected to change in the future). However, new calibration protocols and methods can achieve better results (e.g. hybrid models) and should be studied further.

The precipitation data used in the hydrological modelling calibration was an important factor and should not be neglected in the uncertainty sampling. The use of good quality model-based precipitation data (e.g., MSWEP) was shown to be as accurate as ground-level Hidroweb observations, and could be useful in data-scarce areas in Brazil.

At the end, the large ensemble was challenging to handle due to the size and complexity. The urge to process this huge amount of data generated in the thesis made the desire of combining the simulations altogether in one value (median, mean) very appealing. However, here we aimed to show that instead of looking for a 'perfect model' (right for the right reasons), more importantly is working with a fit-to-purpose model, and for that, the individual members of the ensemble should not be combined in a single estimate in the early stages of the modelling process.

While this study does not allow conclusive evidence that a fitness-for-purpose ensemble weighting system outperforms mean and median ensemble estimates, it clearly demonstrates that taking into account the strengths of different ensemble members can lead to a better estimate of specific purpose-variables, and its promising incorporating user-centred modelling in climate change impact assessments under large uncertainty. Along with that, there is an urgency to better communicate the large uncertainties so end-users (decision makers, policy makers) can make better decisions.

8 FUTURE RESEARCH

As a fruit of this research, many other topics were found to be interesting and could be developed further to expand the results of this thesis:

- Testing other data-driven methods or the use of hybrid models to predict river discharge under changing conditions, as well as different calibration protocols; including hydrological models of different structures in the climate change impact assessment framework. Paper III and Paper IV
- Testing the impact of a fitness-for-purpose ensemble weighting system on more catchments of diverse hydrological characteristics, as well as testing on risk related to climate change impacts on water resources. Paper IV

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APPENDIX A: Paper I: Incertezas e impactos de mudanças climáticas nos recursos hídricos

IAHR **AIIH**
XXVIII CONGRESO LATINOAMERICANO DE HIDRÁULICA
BUENOS AIRES, ARGENTINA, SEPTIEMBRE DE 2018

INCERTEZAS E IMPACTOS DE MUDANÇAS CLIMÁTICAS NOS RECURSOS HÍDRICOS

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RESUMO: As mudanças climáticas poderão ter graves consequências nos recursos hídricos, como variações na disponibilidade hídrica, redução e/ou aumento de vazões e aumento na ocorrência de eventos extremos. Neste contexto, a adaptação da sociedade às mudanças climáticas é indispensável, o que exige a compreensão de seus impactos e o planejamento por parte dos tomadores de decisão. Atualmente, uma das abordagens existentes para avaliar os impactos das mudanças climáticas nos recursos hídricos consiste em realizar projeções hidrológicas com base em cenários de modelagem climática futura. Contudo, existem diversas fontes de incertezas que podem ser consideradas nesse método, provenientes dos cenários de emissões de gases do efeito estufa, dos modelos climáticos, da técnica de remoção de viés e da modelagem hidrológica, que podem impactar nos resultados obtidos, e consequentemente, interferir na qualidade das ações e planos de adaptação. O objetivo deste trabalho é apresentar o estado da arte quanto às incertezas inerentes aos estudos de mudanças climáticas e principais métodos que têm sido utilizados na sua quantificação. Esse conhecimento pode levar a uma nova visão do processo de modelagem hidrológica em estudos de mudança climática, promovendo uma compreensão de meios que aumentem a robustez dos estudos futuros e a confiabilidade das projeções.

ABSTRACT: Climate change may have serious consequences on water resources, such as variations in water availability, reduction and/or increase in flows and increase in the occurrence of extreme events. In this context, the adaptation of society to climate change is indispensable, which requires the understanding of its impacts and the planning by the decision makers. One of the current approaches to assessing the impacts of climate change on water resources is to carry out hydrological projections based on future climate modeling scenarios. However, there are several sources of uncertainties that can be considered in this method, from the scenarios of greenhouse gas emissions, climate models, bias removal techniques and hydrological modeling, which may have an impact on the results obtained, and consequently, to prejudice the quality of actions and adaptation plans. The aim of this work is to present the state of the art regarding the uncertainties inherent in the studies of climate change and main methods that have been used in its quantification. This knowledge can lead to a new view of the hydrological modeling process in climate change studies, promoting an understanding of ways that increase the robustness of future studies and the reliability of projections.

PALAVRAS-CHAVE: confiabilidade; métodos estatísticos; projeção hidrológica

INTRODUÇÃO

Diversos estudos têm mostrado que as mudanças climáticas poderão ter graves impactos nos recursos hídricos disponíveis em todo o mundo, como variações na disponibilidade hídrica, aumento e/ou redução de vazão, e aumento na ocorrência de eventos extremos, que variam dependendo da localização geográfica (Milly; Dunne; Vecchia, 2005). Por isso, a adaptação da sociedade às mudanças climáticas é indispensável, o que exige a compreensão de seus impactos e o planejamento por parte dos tomadores de decisão.

Modelos chuva-vazão combinados com cenários de mudanças climáticas são amplamente utilizados para avaliar o impacto das mudanças do clima na escala de bacias hidrográficas, o que requer projeções climáticas realistas e modelos hidrológicos robustos, que produzam informações confiáveis em condições climáticas variáveis. Contudo, existem diversas fontes de incertezas que podem ser consideradas nessa abordagem, provenientes dos cenários de emissões de gases do efeito estufa, dos modelos climáticos globais e regionais, da técnica de *downscaling* usada para trazer a informação à escala da bacia hidrográfica e do modelo hidrológico utilizado (Wilby, 2005).

O conhecimento sobre as incertezas inerentes aos estudos de impacto das mudanças climáticas, permite obter uma visão consistente de como os resultados devem ser interpretados e possibilita a obtenção de informações mais confiáveis sobre a resposta hidrológica, como média, desvio padrão, níveis e intervalos de confiança e a probabilidade de exceder certo valor crítico, como vazões máximas ou mínimas (Webster; Sokolov, 2000).

No Brasil, sua quantificação em estudos de impactos das mudanças climáticas não é prática frequente, e quando é abordada, geralmente considera somente àquelas relativas aos modelos climáticos e cenários e negligencia outras fontes (Adam, 2016). Uma forma de abordá-la na previsão e tomada de decisão na área de hidrologia é a partir da utilização de previsões probabilísticas, obtidas na forma de previsões por conjunto (ou por *ensemble*). Nesta modalidade de previsões, geralmente são gerados diversos cenários futuros possíveis, com o objetivo de reduzir o erro de previsão, oriundo de apenas um resultado determinístico (Fan, Ramos, Collischonn, 2015).

A média ou a mediana do conjunto das projeções do modelo é muitas vezes defendida como uma representação útil do futuro. No entanto, uma questão importante que deveria ser levantada é, e se a maioria (ou todos) os modelos se revelarem errados na projeção de uma mudança na variável de interesse? Como apontaram Fan e Collishonn (2015), não se tem uma compreensão completa do benefício e necessidade da consideração de todas as fontes de incertezas existentes no processo de previsão nos sistemas hidrológicos de previsão por conjunto, no entanto é consensual que ao menos, deveriam ser encorajadas pesquisas que avaliem os benefícios econômicos em setores dependentes de condições climáticas futuras (hidroeletricidade, irrigação, navegação, etc).

Os estudos conduzidos em bacias brasileiras que abordaram algumas dessas fontes concluíram que as alterações nas vazões e disponibilidade hídrica podem variar de acordo com o modelo climático utilizado, método de *downscaling* e/ou cenários de emissão, obtendo-se resultados divergentes entre aumento e redução das variáveis sob o efeito de mudanças climáticas em um mesmo local estudado (Adam; Collischonn, 2013, Bravo et al., 2013, Paiva; Collischonn, 2010, Nóbrega et al., 2010). Dessa forma, salienta-se a importância da análise e quantificação nesses estudos, auxiliando na projeção de impactos confiáveis que subsidiem a gestão de recursos hídricos, planejamento energético e de outros setores ligados à disponibilidade de água.

MODELOS E CENÁRIOS DE PROJEÇÃO CLIMÁTICA

Nos últimos anos, séries históricas de variáveis climáticas, tais como temperatura do ar e precipitação, são estudadas em diversas regiões do mundo, para testar hipóteses de que existem alterações no comportamento do clima. Previsões do Painel Intergovernamental sobre Mudanças Climáticas (IPCC) sugerem que pode haver um aumento acima de 2°C na temperatura média global e uma alteração na distribuição da precipitação no mundo, decorrente das concentrações elevadas dos Gases de Efeito Estufa (GEE), caso estes continuem a ser produzidos a taxas crescentes (IPCC, 2007).

Projeções de cenários de mudanças climáticas a longo prazo, com alta resolução, são realizadas em Modelos Climáticos Regionais (RCM) a partir de *downscaling* de Modelos Climáticos Globais (GCM) (Chou et al., 2014). Para a realização de projeções do clima, os modelos do sistema terrestre são forçados por um conjunto de condições de contorno determinadas por cenários de emissões antropogênicas de dióxido de carbono e outros gases radiativamente ativos (Sampaio; Dias, 2014). As emissões antropogênicas de gases do efeito estufa são principalmente motivadas pelo tamanho da população, atividade econômica, estilo de vida, uso de energia, padrões de uso da terra, tecnologias e políticas climáticas.

As alterações climáticas projetadas pelos modelos climáticos, caracterizadas em função da emissão de gases e o aumento do efeito estufa, se refletem na modificação de variáveis representativas do clima, tais como precipitação, temperatura do ar, umidade do ar, vento, radiação solar, entre outras. Essas projeções servem como base para a aplicação em modelos hidrológicos que estimam as possíveis mudanças nas variáveis de interesse em recursos hídricos.

Os cenários utilizados para projeções climáticas, até o 4º Relatório de Avaliação (AR4) das Mudanças Climáticas, são nomeados pelas famílias A1, A2, B1 e B2, provenientes do Relatório Especial sobre Cenários de Emissão (SRES), divulgado nos anos 2000 pelo IPCC (Quadro 1).

Quadro 1. – Descrição dos cenários provenientes do Relatório Especial sobre Cenários de Emissão (SRES, 2000), famílias A1, A2, B1 e B2.

Cenário	Descrição
A1	Mundo futuro de crescimento econômico muito rápido, população global atinge um pico em meados do século e declina em seguida, rápida introdução de tecnologias novas e mais eficientes. A família de cenários A1 se desdobra em três grupos que descrevem direções alternativas da mudança tecnológica no sistema energético. Os três grupos A1 distinguem-se por sua ênfase tecnológica: A1FI: intensivo uso de combustíveis fósseis; A1T: fontes energéticas não-fósseis; A1B: equilíbrio entre todas as fontes.
A2	Mundo muito heterogêneo. Caracterizado pela autossuficiência e a preservação das identidades locais. Os padrões de fertilidade entre as regiões convergem muito lentamente, o que acarreta um aumento crescente da população. O desenvolvimento econômico é orientado primeiramente para a região, sendo que o crescimento econômico *per capita* e a mudança tecnológica são mais fragmentados e mais lentos do que nos outros contextos.
B1	Mundo convergente com a mesma população global, que atinge o pico em meados do século e declina em seguida, como no contexto A1, mas com uma mudança rápida nas estruturas econômicas em direção a uma economia de serviços e informações, com reduções da intensidade material e a introdução de tecnologias limpas e eficientes em relação ao uso dos recursos. A ênfase está nas soluções globais para a sustentabilidade econômica, social e ambiental, inclusive a melhoria da equidade, mas sem iniciativas adicionais relacionadas com o clima.
B2	Mundo em que a ênfase está nas soluções locais para a sustentabilidade econômica, social e ambiental. É um mundo em que a população global aumenta continuamente, a uma taxa inferior à do A2, com níveis intermediários de desenvolvimento econômico e mudança tecnológica menos rápida e mais diversa do que nos contextos B1 e A1. O cenário também está orientado para a proteção ambiental e a equidade social, mas seu foco são os níveis local e regional.

Fonte: IPCC, 2000.

A partir do 5º Relatório de Mudanças Climáticas (IPCC, 2013) foram criados quatro diferentes cenários de projeções para representar as consequências climáticas até o final do século XXI, denominados de Caminhos Representativos de Concentração (RCP), relacionados às concentrações equivalentes de CO_2 na atmosfera. O termo "caminho" enfatiza que não só os níveis de concentração de CO_2 a longo prazo são de interesse, mas também a trajetória tomada ao longo do tempo para alcançar esse resultado, e a palavra "representativo" significa que cada RCP fornece apenas um dos muitos cenários possíveis que levariam às características de forçamento radiativo específico (Moss et al., 2010). A descrição dos cenários RCPs é apresentada no Quadro 2.

Quadro 2. - Descrição dos cenários RCPs.

Cenário	Forçante radiativa	Concentração (ppm)	Caminho	Modelo
RCP 8.5	> 8.5 Wm^{-2} em 2100	> 1,370 CO_2 equiv. em 2100	Aumento	MESSAGE
RCP 6.0	~ 6 Wm^{-2} com estabilização após 2100	~ 850 CO_2 equiv. (com estabilização após 2100)	Estabilização sem superação	AIM
RCP 4.5	~ 4.5 Wm^{-2} com estabilização após 2100	~ 650 CO_2 equiv. (com estabilização após 2100)	Estabilização sem superação	GCAM
RCP 2.6	Pico de ~3Wm^{-2} antes de 2100 e depois declínio	Pico de ~ 490 CO2-equiv. antes de 2100 e depois declínio	Pico e declínio	IMAGE

Fonte: MOSS et al., 2010.

Os RCPs incluem um cenário de mitigação rigoroso (RCP 2.6), dois cenários intermediários (RCP 4.5 e RCP 6.0) e um cenário com emissões de GEE muito altas (RCP 8.5). Comparando as concentrações de dióxido de carbono e a variação da temperatura global entre os cenários SRES e RCP, SRES A1FI é semelhante ao RCP 8.5, SRES A1B ao RCP 6.0 e SRES B1 ao RCP 4.5. O cenário do RCP 2.6 é representativo de um cenário que visa manter o aquecimento global abaixo de 2°C acima das temperaturas pré-industriais (IPCC, 2014) porque inclui a opção de usar políticas para alcançar emissões líquidas negativas de dióxido de carbono antes do final do século, o que não acontece nos cenários SRES.

Apesar do grande avanço científico e computacional que proporcionou maior entendimento do sistema climático e permite a projeção de cenários de mudanças climáticas, ainda há grande incerteza inerente a esses dados (IPCC, 2000), principalmente na escala regional, sendo algumas variáveis mais confiáveis (temperatura) que outras (precipitação, por exemplo) (Santos et al., 2015).

Os modelos climáticos podem não representar perfeitamente o clima atual devido principalmente à influência da discretização espacial dos modelos e erros sistemáticos causados pela conceituação imperfeita dos fenômenos e processos que governam o clima (Oliveira; Pedrollo; Castro, 2015, Teutschbein; Seibert, 2012). Além de erros sistemáticos na modelagem de clima, existem outras fontes de incertezas como àquelas provenientes das emissões futuras de gases de efeito estufa, aerossóis e atividades vulcânicas e solares, inclusão de efeitos diretos do aumento na concentração de CO_2 atmosférico nas plantas e do efeito do comportamento das plantas no clima futuro e sensibilidade do clima global e padrões regionais das projeções do clima futuro simulado pelos modelos, devido às diferentes formas em que cada modelo de circulação geral da atmosfera representa os processos físicos e os mecanismos do sistema climático (Marengo, 2006).

Diante disso, alguns estudos buscam quantificá-las a partir da utilização de simulações por conjunto (*emsemble*) de diversos GCMs e/ou RCMs e cenários de emissão, nas quais os resultados das previsões são sintetizados em uma média simples, onde para cada membro é atribuído igual probabilidade de ocorrência ou a partir da utilização de aproximações probabilísticas. Na aproximação probabilística, os resultados de diferentes modelos ou integrações de um mesmo modelo são utilizados para a produção de uma Função Densidade de Probabilidade (FDP) ou uma Função Distribuição Acumulada (FDA), no qual a amplitude das curvas representa uma medida da incerteza na projeção, e a integral entre dois limiares estabelecidos indicam a probabilidade de sua ocorrência (Santos et al., 2015).

MODELAGEM HIDROLÓGICA

A modelagem hidrológica apresenta-se como uma ferramenta essencial de análise para representar um sistema (bacia hidrográfica) no todo ou em partes, o comportamento de um processo hidrológico ou conjunto de processos, em um dado instante ou intervalo de tempo (Moreira, 2005). Atualmente, modelos hidrológicos têm sido utilizados para realizar projeções dos impactos das mudanças climáticas nos recursos hídricos em nível de bacias hidrográficas a partir de cenários climáticos fornecidos por GCMs e/ou RCMs (Amin et al., 2017, Chilkoti; Bolisetti; Balachandar, 2017, Zhang et al., 2014). A transferência dos dados de projeção climática para um modelo hidrológico tem a função de projetar o estado dos componentes da fase atmosférica para a fase terrestre do ciclo hidrológico da bacia.

Um dos produtos da modelagem hidrológica com base em cenários de mudanças climáticas é a estimativa da frequência no futuro de eventos importantes para a gestão de recursos hídricos, como por exemplo, vazões baixas que podem prejudicar a produção de energia ou sistemas de irrigação, assim como enchentes que podem danificar infraestruturas e impactar a sociedade.

Uma vez apresentadas as incertezas inerentes às projeções climáticas, é necessário destacar que estas se propagam para a modelagem hidrológica. Por exemplo, se os cenários utilizados tendem a superestimar as temperaturas no futuro, um impacto hidrológico poderia ser um aumento na evapotranspiração da bacia hidrográfica, indicando um cenário mais drástico que a realidade.

Ainda, existem as fontes próprias da modelagem hidrológica em condições estacionárias (condições climáticas e/ou características físicas), que incluem erros na estrutura do modelo, problemas no processo de calibração, e erros nos dados utilizados para a calibração (Brigode; Oudin; Perrin, 2013). Em condições não estacionárias, como em estudos de mudanças climáticas, adicionam-se ainda a instabilidade de parâmetros, que podem ocorrer devido às possíveis alterações nas características físicas e de captação nos processos dominantes. Os erros de estrutura do modelo e a estabilidade de seus parâmetros são consideradas como as duas principais fontes na etapa de modelagem hidrológica (Adam, 2016). Para a quantificação dos erros inerentes à modelagem hidrológica (estrutura), o método geral consiste em avaliar a resposta hidrológica de diferentes modelos chuva-vazão, numa abordagem de simulação por conjunto (Wilby; Harris, 2006).

INCERTEZAS DAS MUDANÇAS CLIMÁTICAS NO RECURSOS HÍDRICOS

Muitos estudos conduzidos ao redor do mundo investigaram o efeito das mudanças climáticas na resposta hidrológica de bacias hidrográficas. As análises de vazões de rios na América do Sul e no Brasil apontam para aumentos entre 2% e 30% na bacia do Rio Paraná e nas regiões vizinhas no Sudeste da América do Sul (Milly; Dunne; Vecchia, 2005), consistente com as análises de tendência de chuva observada na região (Marengo, 2008). No entanto, a maioria desses estudos não abordam a quantificação das incertezas associadas aos resultados apresentados, ainda que seja fundamental para o desenvolvimento de planos e estratégias de adaptação robustos, reduzindo os riscos associados às decisões em recursos hídricos.

Existe um consenso na literatura sobre a importância relativa das diferentes fontes de incerteza. Os resultados indicam que o GCM domina outras fontes em estudos de impacto hidrológico (Wilby; Harris, 2006, Prudhomme; Davies, 2009, Kay et al., 2009, Arnell, 2011). No entanto, alguns estudos afirmam que a previsão dos modelos hidrológicos pode estar na mesma faixa de importância ou até maior que a climática (Goderniaux et al., 2015, Dams et al., 2015, Zhang; Xu; Fu, 2014, Bastola et al., 2011). Ainda, a importância dessas fontes pode variar temporalmente e sob a escala de análise escolhida (Shrestha et al., 2016) e variável em análise (vazões baixas ou vazões altas) (Meresa; Romanowicz, 2016).

Atualmente, as abordagens adotadas para o estudo de impacto das mudanças climáticas incluem a avaliação sem qualquer quantificação desse parâmetro (Gosain; Rao; Basuray, 2006; Thodsen, 2007), focam apenas na climática e negligenciam a hidrológica (Woldemeskel; Sharma; Mehrotra, 2014) ou mesmo tomam uma única projeção climática e avaliam apenas a hidrológica (Steele-Dunne et al., 2008).

A análise multi-propagação é utilizada para detectar a incerteza total do conjunto, em vez da análise de propagação única, na qual os elementos de uma única fonte são variados enquanto os de outras são estáticos. Esta análise considera todas as combinações possíveis de elementos entre as fontes e as contribuições de cada uma para a estimativa total e os efeitos das interações entre as fontes podem ser decompostos, por exemplo, por análise de variância (Meresa; Romanowicz, 2016, Addor et al., 2014). Exemplos de estudos que contemplaram a análise de diversas fontes de incerteza como modelos climáticos, cenários de emissão e modelagem hidrológica foram os trabalhos conduzidos por Meresa e Romanowicz, 2017, Addor et al, 2014 e Minville et al., 2008.

Estudos em bacias hidrográficas brasileiras têm utilizado diferentes modelos climáticos globais para estimar os impactos de mudanças climáticas, no entanto poucos têm avaliado a influência das demais fontes de incertezas. Uma síntese de trabalhos publicados no Brasil que avaliaram os impactos de mudanças climáticas contemplando essa análise é apresentada no trabalho de Adam (2016), o qual aponta as divergências nos resultados. Adam et al. (2015) concluíram que os impactos do cenário A1B sobre as vazões da bacia do Paraná são altamente dependentes do membro de perturbação do modelo utilizado para obter as projeções climáticas e na maioria dos casos as vazões máximas projetadas estão dentro dos limites de incerteza em relação às series atuais. Os resultados apontaram que a variabilidade natural do clima pode ser tão importante quanto a influência de mudanças climáticas e a incerteza aumenta com a ampliação do horizonte de tempo analisado.

ANÁLISE E QUANTIFICAÇÃO DAS INCERTEZAS

Processos que não são totalmente compreendidos, e cujos resultados não podem ser previstos com precisão, frequentemente são denominados incertos. A incerteza é atribuída à falta de informações perfeitas sobre os fenômenos, processos e dados envolvidos na definição e resolução de um problema, condição gerada pela falta de controle sobre a ocorrência de determinados eventos (Mays; Tung, 1992).

É importante enfatizar a diferença entre o termo erro e incerteza, o primeiro expressa a diferença entre um valor simulado ou medido e o valor verdadeiro, enquanto o outro está associado ao sentido probabilístico, uma vez que trata da variação nos resultados de um evento aleatório, dos distúrbios derivados de considerações errôneas ou da distribuição de erros associados com as quantidades observadas ou estimadas. A maioria das entradas e saídas de processos na área de recursos hídricos não são conhecidas com certeza. Por isso, ignorar esse fator em estudos hidrológicos pode levar a conclusões incorretas sobre os fenômenos que se buscam representar (Loucks; Van Beek, 2005).

Os fenômenos naturais, incluindo os hidrológicos, contêm incertezas que lhes são inerentes sendo que existem duas fontes: (i) a aleatoriedade natural associada às possíveis ocorrências (ou realizações) de um certo fenômeno; e (ii) as imperfeições e/ou insuficiências do conhecimento humano sobre os processos que determinam tais ocorrências. As aleatórias, podem ser expressas em termos da maior ou menor variabilidade de uma ou mais das variáveis (ou grandezas mensuráveis) associadas ao fenômeno em estudo. Já as do segundo tipo resultam da interpretação imperfeita ou imprecisa da realidade subjacente ao referido fenômeno, por parte dos modelos teóricos e/ou físicos utilizados para o caracterizar (Naghettini; Portela, 2011).

Em resumo, em todas as situações reais, não se conhece o valor verdadeiro da grandeza que se pretende conhecer, e por isso é então necessário obter a melhor representação desse valor verdadeiro e a incerteza associada a este erro. Uma boa estimativa do valor verdadeiro da grandeza pode ser obtida a partir da repetição dos experimentos, sendo a melhor estimativa obtida da média dos resultados dos experimentos. Contudo, a repetição dos experimentos auxilia no controle de erros aleatórios, mas não dos erros sistemáticos. Estes dois erros devem ser combinados para a estimativa do erro final.

A análise da incerteza em hidrosistemas ou seus componentes requer o uso de probabilidade e estatística. Uma forma de análise é baseada no conceito de intervalo de confiança, sendo que este é um intervalo estimado de um parâmetro de interesse de uma população. Em vez de estimar o parâmetro por um único valor, é dado um intervalo de estimativas prováveis. O quanto estas estimativas são prováveis será determinado pelo coeficiente de confiança $(1-\alpha)$, para $\alpha \in (0,1)$.

Intervalos de confiança (IC) são usados para indicar a confiabilidade de uma estimativa. Por exemplo, sendo todas as estimativas iguais, uma pesquisa que resulte num IC pequeno é mais confiável do que uma que resulte num IC maior. O IC depende do desvio padrão e da distribuição estatística do fenômeno, sendo que o Teorema do Limite Central afirma que a soma de muitas variáveis independentes aleatórias e com mesma distribuição de probabilidade sempre tende a uma distribuição normal.

De acordo com Vuolo (2008), as principais formas para indicar a incerteza são: incerteza padrão (σ), incerteza expandida com confiança P ($k\sigma$), limite de erro (L) e erro provável (Δ). O parâmetro σ pode ser definido como o desvio padrão da distribuição dos erros, já $k\sigma$ é um múltiplo da incerteza padrão. O parâmetro L é o valor máximo admissível para o erro e erro provável é o valor Δ que tem 50% de probabilidade de ser excedido pelo erro η, em módulo, porém este indicador não é muito usado atualmente.

Além das incertezas individuais, é conveniente estimar a propagação destas em uma grandeza w (x, y, z,...), a partir das σ_x, σ_y, σ_z,... e das covariâncias associadas às grandezas x, y, z,...

A análise multi-propagação pode ser utilizada para detectar a estimativa total do conjunto (isto é, incerteza geral nas avaliações de mudanças climáticas), em vez da análise de propagação única, na qual os elementos de uma única fonte são variados enquanto os de outras são estáticos. Esta análise considera todas as combinações possíveis de elementos entre as fontes e suas contribuições para a estimativa geral e os efeitos das interações entre elas (Meresa; Romanowicz, 2016, Addor et al., 2014).

Segundo Vuolo (2008), se os erros nas variáveis x, y, z,... são completamente independentes entre si, σ em w (Equação 1) é, em primeira aproximação, dada por:

$$\sigma_w{}^2 = \left(\frac{\partial w}{\partial x}\right)^2 \sigma_x{}^2 + \left(\frac{\partial w}{\partial y}\right)^2 \sigma_y{}^2 + \left(\frac{\partial w}{\partial z}\right)^2 \sigma_z{}^2 + \cdots \qquad [1]$$

Uma expressão mais completa quando os erros não são completamente independentes é dada pela Equação 2.

$$\sigma_\omega{}^2 = \left(\frac{\partial w}{\partial x}\right)^2 \sigma_x{}^2 + \left(\frac{\partial w}{\partial y}\right)^2 \sigma_y{}^2 + \left(\frac{\partial w}{\partial z}\right)^2 \sigma_z{}^2 + \cdots + 2\left(\frac{\partial w}{\partial x}\right)\left(\frac{\partial w}{\partial y}\right)\sigma_{xy}{}^2 +$$
$$+2\left(\frac{\partial w}{\partial x}\right)\left(\frac{\partial w}{\partial z}\right)\sigma_{xz}{}^2 + +2\left(\frac{\partial w}{\partial y}\right)\left(\frac{\partial w}{\partial z}\right)\sigma_{yz}{}^2 + \cdots \qquad [2]$$

A equação geral para propagação de incerteza fornece uma informação importante acerca do quanto uma determinada variável influi na precisão final da quantidade chave. A sensibilidade é dada pelo termo da Equação 3, sendo que quanto maior o valor de S_i, maior será o peso daquela variável no resultado final.

$$S_i = \frac{\partial f}{\partial xi} \qquad [3]$$

ANÁLISE DE VARIÂNCIA

A utilização da Análise de Variância (ANOVA) tem sido uma técnica frequentemente utilizada (Meresa; Romanowics, 2017, Vetter et al., 2017, Addor et al., 2014, Bosshard et al., 2013). Na abordagem ANOVA, escolhe-se a variância da projeção como uma estimativa de sua incerteza e quantifica-se a contribuição das diferentes fontes para a incerteza total (Addor et al., 2014).

Meresa e Romanowicks utilizaram ANOVA para identificar a contribuição relativa de cada fonte, correspondente aos conjuntos de parâmetros (P), modelos climáticos (C) e conjuntos de distribuição de parâmetros (D), a partir do espalhamento da mudança do quantil de vazão no futuro próximo e distante, segundo o modelo ANOVA descrito na Equação 4.

$$T_{ijk} = \mu + P_i + C_j + D_k + (P + C)_{ij} + (P + D)_{ik} + (C + D)_{jk} + \varepsilon_{ijk} \quad [4]$$

Em que T_{ijk} é o erro total da soma quadrada para o indicador hidrológico extremo específico (por exemplo, mudança relativa no quantil de vazões máximas no período de retorno de 30 anos), para o i-ésimo conjunto de parâmetros, j-ésimo modelo climático e k-ésimo intervalo de distribuição de parâmetros, μ é a média geral, e ε_{ijk} denota o erro branco de Gauss.

MODELO DA MÉDIA BAYESIANA

Outro modelo que pode ser empregado é o Modelo de Média Bayesiana (BMA), que combina distribuições preditivas de diferentes fontes de incerteza. A aplicação deste modelo está crescendo em projeções *emsemble* para produzir projeções médias e probabilísticas de impactos de mudanças climáticas.

Neste método, a Função Densidade de Probabilidade (FDP) de qualquer variável de interesse é uma média ponderada de FDPs centradas nas previsões individuais, onde os pesos são iguais às probabilidades posteriores dos modelos que geram as previsões, e reflete em contribuições relativas dos modelos para a habilidade preditiva no período de treinamento. Os pesos do BMA podem ser usados para avaliar a utilidade dos membros do grupo, e isso pode ser usado como base para selecionar os membros do conjunto para previsão (Bastola; Murphy; Sweeney, 2011).

A descrição que segue refere-se a metodologia empregada por Bastola et al. (2011), para aplicação do BMA.

Na situação em que vários modelos $\{f_1, . ., f_k\}$ são teoricamente possíveis, é arriscado basear a inferência nas estimativas pontuais de um único modelo f_k. BMA permite contabilizar este tipo de incerteza a partir da distribuição preditiva da quantidade de interesse (Equação 5), o cálculo é feito a partir da média da distribuição preditiva posterior da quantidade derivada de cada modelo individual ponderada pelas correspondentes probabilidades posteriores do modelo.

$$p(\Delta|f_1, \dots, f_k, D) = \sum_{k=1}^{K} p(\Delta|f_k, D)p(f_k|D) \quad [5]$$

A probabilidade posterior do modelo $p(f_k|D)$ do modelo f_k de acordo com os dados é pela Equação 6.

$$p(f_k|D)\alpha p(D|f_k)p(f_k) \quad [6]$$

Em que a constante de proporcionalidade é escolhida de modo que o modelo de probabilidade posterior some um. A probabilidade anterior, p(f_k), na Equação 6 apresenta a preferência do modelo f_k antes da reavaliação. Portanto, um modelo com histórico de melhor desempenho terá um maior peso na aplicação futura. Note-se que sem qualquer conhecimento prévio da preferência do modelo, a probabilidade anterior é assumida como tendo uma distribuição uniforme entre os modelos N. A quantidade p (D|f_k) é a probabilidade integrada do modelo f_k.

A média e a variância posterior de Δ são apresentadas nas Equações 7 e 8, respectivamente.

$$E[\Delta|f_1,\dots,f_k,D)] = \sum_{k=1}^{K} w_k\,\widehat{\Delta_k} \qquad [7]$$

$$Var[\Delta|f_1,\dots,f_k,D)] = \sum_{k=1}^{K}(Var(\Delta|D,f_k) + \widehat{\Delta_k})w_k - E(\Delta|D)^2 \qquad [8]$$

Em que $\widehat{\Delta_k} = (E\Delta|D,f_k)$. Note-se que peso $w_k$tem um valor apenas entre 0 e 1. Um valor maior indica maior preferência na predição. Nesta aplicação, a FDP de cada modelo no momento t é modelado por uma distribuição gama (Equação 9) com variância heteroscedástica (Equação 10).

$$p(\Delta|f_k) = \Delta^{\alpha_k - 1} e^{\left(\frac{\Delta}{\beta_k}\right)} / (\Gamma(\alpha_k)\Theta^{\alpha_k}) \qquad [9]$$

$$\alpha = \frac{{\mu_k}^2}{{\sigma_k}^2}; \beta_k = \frac{{\sigma_k}^2}{\mu_k};\ \mu_k = f_k; {\sigma_k}^2 = b.f_k + c \qquad [10]$$

$$l(w_1,\dots,w_k|{\sigma_1}^2,\dots,{\sigma_k}^2,\Delta) = \sum_{t=1}^{n}\log\left(w_1\,p(\Delta|f_1) + \dots + w_k p(\Delta|f_k)\right) \qquad [11]$$

Onde b e c na Equação 10 são os coeficientes que relacionam a saída do modelo com as variações do modelo. Como a vazão é diferente de zero e a distribuição da vazão diária é altamente distorcida, a FDP de cada modelo é modelada usando distribuição gama. Em cada passo do tempo, a FDP escolhida é centrada nas previsões individuais com uma variância associada que é heterocedástica e depende diretamente na previsão da vazão real. Os parâmetros do BMA, ou seja, pesos e variâncias, podem ser obtidas a partir da vazão observada histórica usando amostragem de *Markov Chain Monte Carlo* (MCMC).

As previsões probabilísticas da vazão diária são derivadas com base em previsões individuais determinísticas obtidas a partir de cada modelo hidrológico e seu peso e variância. O procedimento utilizado por Bastola (2011) para gerar previsões probabilísticas para cada etapa de tempo t é descrito abaixo:

Etapa 1: Selecionar os modelos k que podem ser estrutural ou parametricamente diferentes.

Etapa 2: Gerar conjuntos de previsão de modelo $\widehat{y_{i,k}}$ $(i = 1,2,\dots,;k = 1,2,\dots,K)$

Etapa 3: Calcular pesos w_k e variância Var_k para cada um dos modelos selecionados.

Etapa 4: Gerar uma nova previsão baseada em modelo $\hat{Y}$ usando a Equação 7.

Etapa 5: As previsões probabilísticas são feitas usando o peso médio (w_k) e parâmetros de variância (Var_k) da seguinte forma:

- Selecionar um modelo concorrente individual (f_k) com probabilidade proporcional ao seu peso.
- Obter amostra da distribuição de probabilidade associada com a saída de cada modelo individual.
- Repetir os dois passos acima para obter uma amostra de vários valores que representam a distribuição da vazão no tempo t e, subsequentemente, derivar o intervalo de incerteza.

CONCLUSÃO

Apesar da análise das incertezas não ser um tema recente na área de mudanças climáticas e hidrologia, muitos estudos não incluem essa análise em seus resultados. No entanto, sem a inclusão desse fator, os estudos podem indicar variações que não representem as condições futuras, e acabar por prejudicar a gestão dos recursos hídricos. A propagação desse parâmetro durante as etapas de aquisição de dados, tratamento dos dados, modelagem e análise dos resultados faz com que as mudanças climáticas ainda sejam foco de especulação e até mesmo, contradição.

Os métodos anteriormente empregados em trabalhos, que avaliavam a incerteza unitária de fontes diversas devem ser substituídos por análises conjuntas, através de métodos como o BMA ou ANOVA. Essa abordagem deveria ser considerada padrão para os estudos de impactos de mudanças climáticas nos recursos hídricos a fim de melhorar a qualidade e confiabilidade dos resultados obtidos, e consequentemente, os planos e ações desenvolvidos pelos tomadores de decisão.

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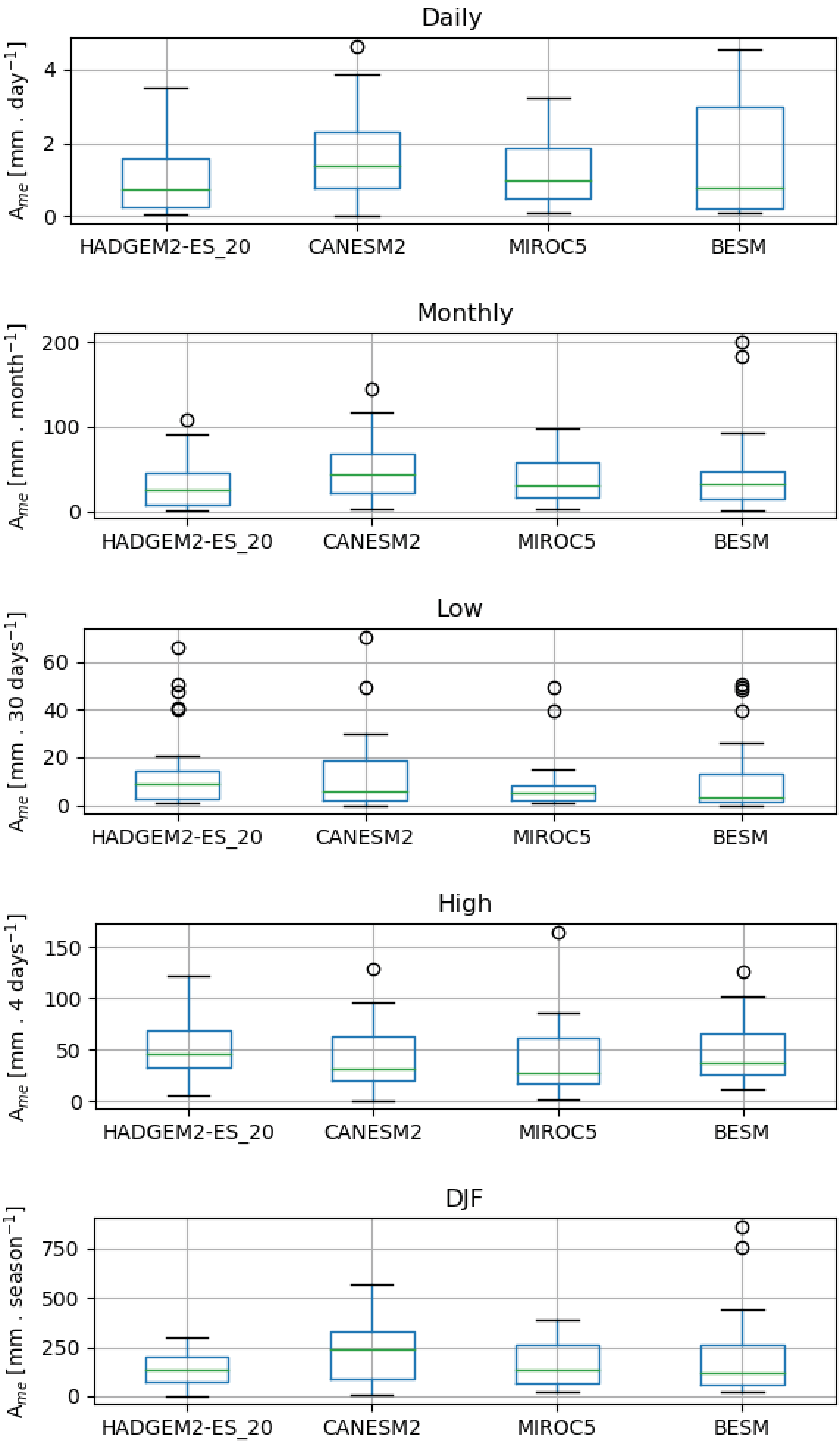
APPENDIX B: Paper II: Supplementary Materials

Supplementary Materials – Paper II

Table S1. Precipitation gauge stations description.

Gauge ID	Gauge name	Hydrografic region	Latitude	Longitude	Altitude (m)	Long - term annual precipitation (mm)
83442	Aracuaí	East Atlantic	-16.83	-42.05	289	686
82571	Barra do Corda	North/Northeast Atlantic	-5.5	-45.23	153	1048
83967	Porto Alegre	Southeast Atlantic	-30.05	-51.16	46.97	1194
83676	Catanduva	Paraná	-21.11	-48.93	570	1215
83669	São Simão	Paraná	-21.48	-47.55	617.39	1295
83581	Florestal	São Francisco	-19.88	-44.41	760	1321
83587	Belo Horizonte	São Francisco	-19.93	-43.93	915	1372
83526	Catalão	Paraná	-18.18	-47.95	840.47	1381
83842	Curitiba	Southeast Atlantic	-25.43	-49.26	923.5	1406
83736	São Lourenço	Paraná	-22.1	-45.01	953.2	1413
83726	São Carlos	Paraná	-21.96	-47.86	856	1437
83781	São Paulo – Mirante de Santana	Paraná	-23.5	-46.61	792.06	1478
83064	Porto Nacional	Tocantins	-10.71	-48.41	239.2	1496
83714	Campos do Jordão	Paraná	-22.75	-45.6	1642	1542
83423	Goiânia	Paraná	-16.66	-49.25	741.48	1556
83630	Franca	Paraná	-20.58	-47.36	1026.2	1557
83374	Goiás	Tocantins	-15.91	-50.13	512.22	1720
82861	Conceição do Araguaia	Tocantins	-8.26	-49.26	156.85	1721
82353	Altamira	Amazon	-3.21	-52.21	74.04	1846
83844	Paranaguá	Southeast Atlantic	-25.53	-48.51	4.5	1896
82113	Barcelos	Amazon	-0.96	-62.91	40	2204
82331	Manaus	Amazon	-3.1	-60.01	61.25	2209
82106	São Gabriel da Cachoeira (UAUPES)	Amazon	-0.11	-67	90	2751
82191	Belém	North/Northeast Atlantic	-1.43	-48.43	10	2790
82141	Soure	Amazon	-0.73	-48.51	10.49	3146
82067	Iauarete	Amazon	0.61	-69.18	120	3266


Daily
A_me [mm . day^-1]
0
2
4
HADGEM2-ES_20
CANESM2
MIROC5
BESM
Monthly
A_me [mm . month^-1]
0
100
200
HADGEM2-ES_20
CANESM2
MIROC5
BESM
Low
A_me [mm . 30 days^-1]
0
20
40
60
HADGEM2-ES_20
CANESM2
MIROC5
BESM
High
A_me [mm . 4 days^-1]
0
50
100
150
HADGEM2-ES_20
CANESM2
MIROC5
BESM
DJF
A_me [mm . season^-1]
0
250
500
750
HADGEM2-ES_20
CANESM2
MIROC5
BESM

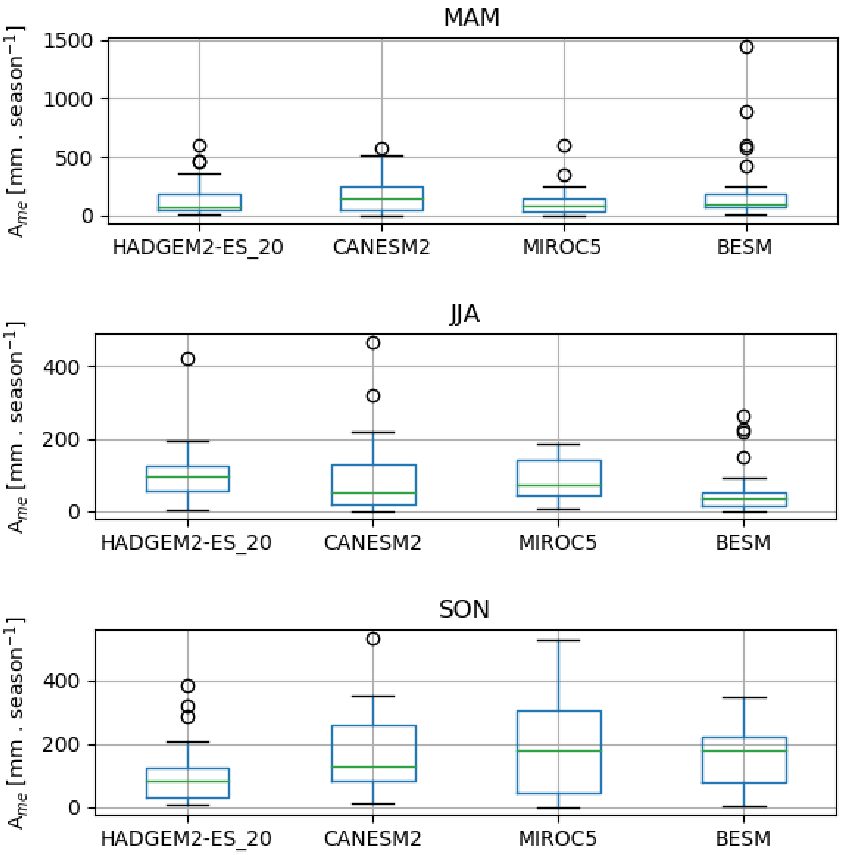
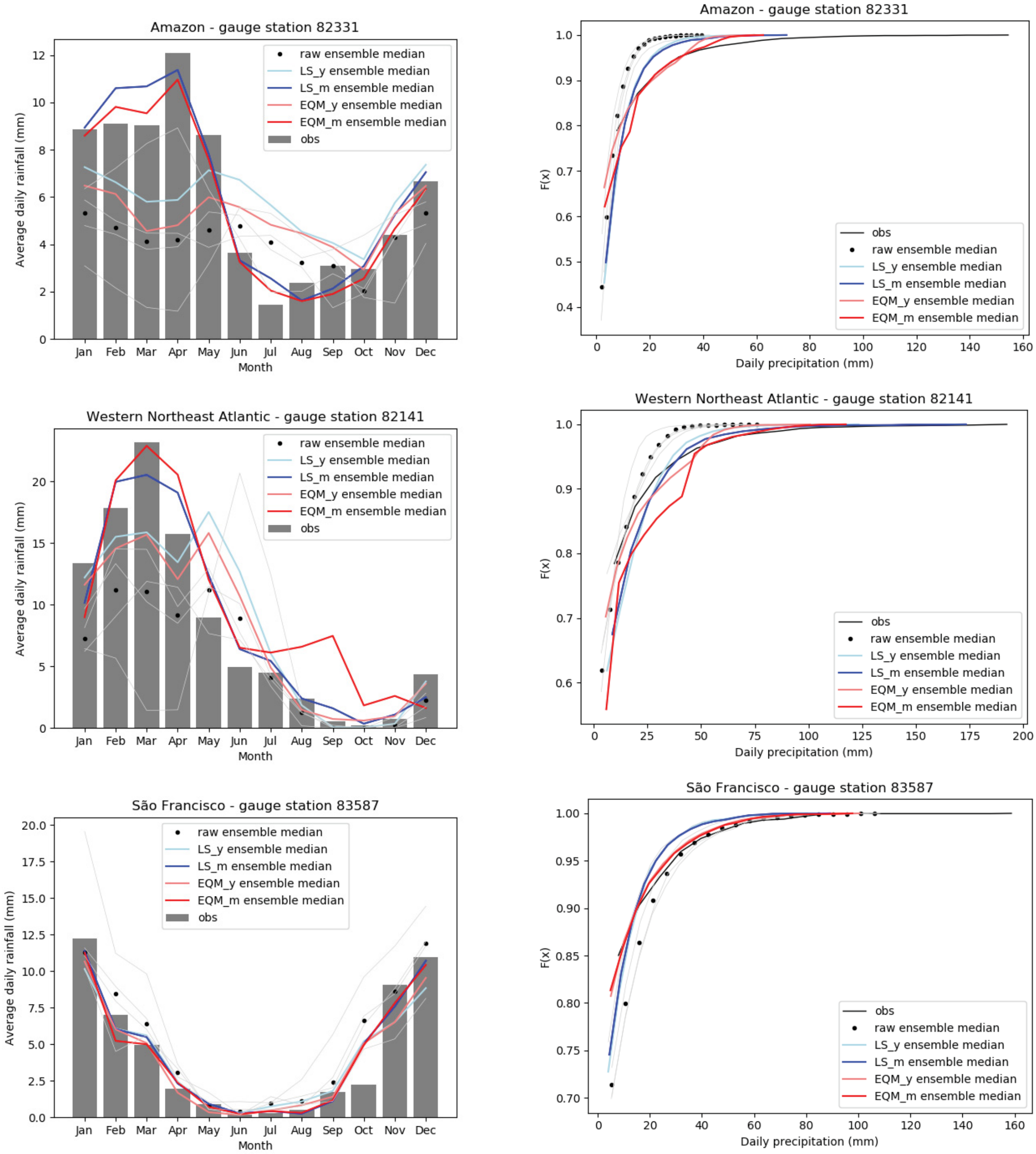
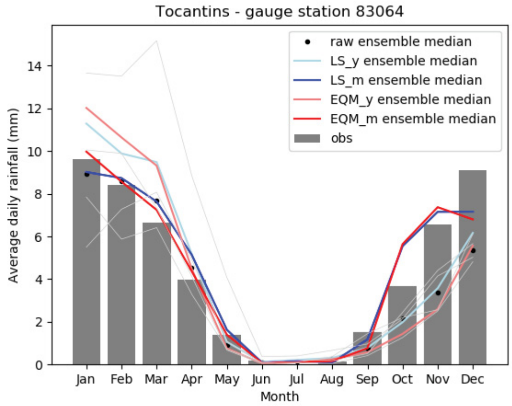
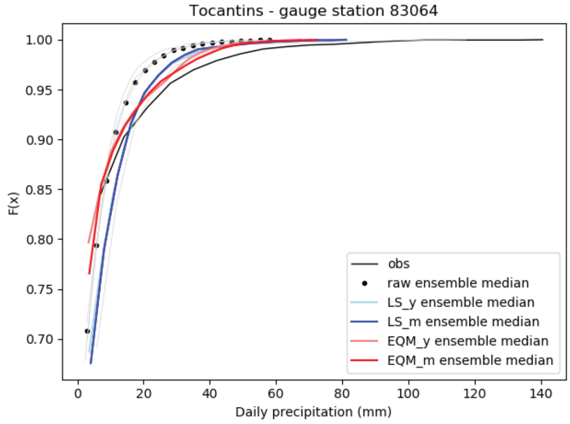
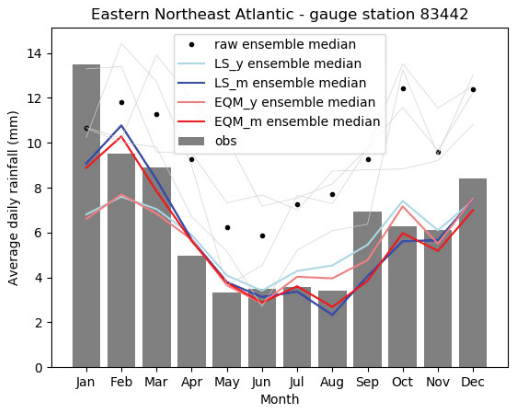


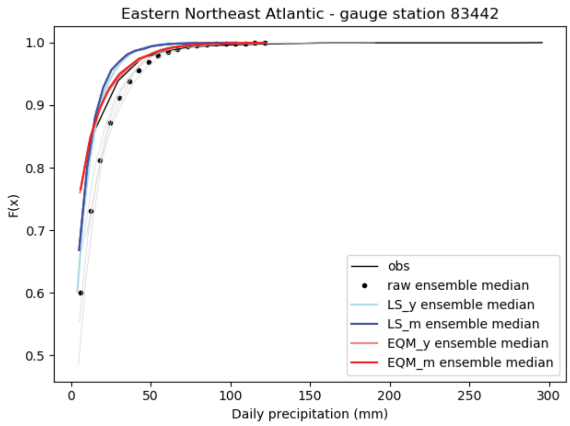
Figure S1. Raw Eta Regional Climate Model performance based on the Absolute value of the Mean Error (A_{me}) for the daily, monthly, low, high and seasonal (DJF, MAM, JJA, SON) precipitation indices across 26 precipitation gauge stations over North, Middle and South Brazil.

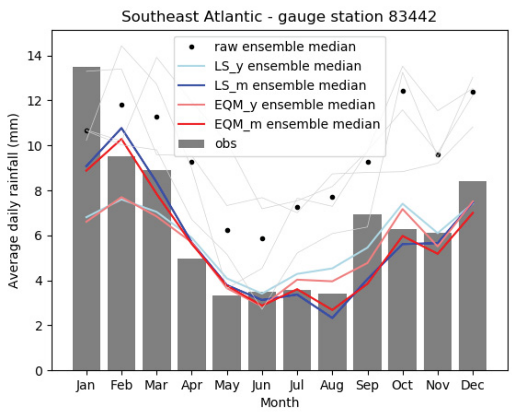

Amazon - gauge station 82331
Average daily rainfall (mm)
Month
Jan Feb Mar Apr May Jun Jul Aug Sep Oct Nov Dec
raw ensemble median
LS_y ensemble median
LS_m ensemble median
EQM_y ensemble median
EQM_m ensemble median
obs
Amazon - gauge station 82331
F(x)
Daily precipitation (mm)
obs
raw ensemble median
LS_y ensemble median
LS_m ensemble median
EQM_y ensemble median
EQM_m ensemble median
Western Northeast Atlantic - gauge station 82141
Average daily rainfall (mm)
Month
raw ensemble median
LS_y ensemble median
LS_m ensemble median
EQM_y ensemble median
EQM_m ensemble median
obs
Western Northeast Atlantic - gauge station 82141
F(x)
Daily precipitation (mm)
obs
raw ensemble median
LS_y ensemble median
LS_m ensemble median
EQM_y ensemble median
EQM_m ensemble median
São Francisco - gauge station 83587
Average daily rainfall (mm)
Month
raw ensemble median
LS_y ensemble median
LS_m ensemble median
EQM_y ensemble median
EQM_m ensemble median
obs
São Francisco - gauge station 83587
F(x)
Daily precipitation (mm)
obs
raw ensemble median
LS_y ensemble median
LS_m ensemble median
EQM_y ensemble median
EQM_m ensemble median

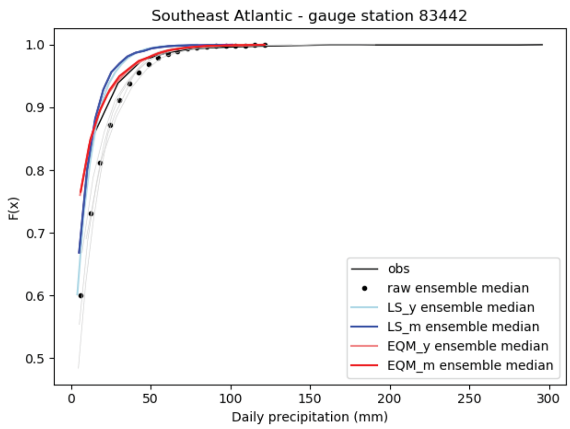

Tocantins - gauge station 83064
Average daily rainfall (mm)
Month
Jan Feb Mar Apr May Jun Jul Aug Sep Oct Nov Dec
raw ensemble median
LS_y ensemble median
LS_m ensemble median
EQM_y ensemble median
EQM_m ensemble median
obs


Tocantins - gauge station 83064
F(x)
Daily precipitation (mm)
obs
raw ensemble median
LS_y ensemble median
LS_m ensemble median
EQM_y ensemble median
EQM_m ensemble median


Eastern Northeast Atlantic - gauge station 83442
Average daily rainfall (mm)
Month
Jan Feb Mar Apr May Jun Jul Aug Sep Oct Nov Dec
raw ensemble median
LS_y ensemble median
LS_m ensemble median
EQM_y ensemble median
EQM_m ensemble median
obs


Eastern Northeast Atlantic - gauge station 83442
F(x)
Daily precipitation (mm)
obs
raw ensemble median
LS_y ensemble median
LS_m ensemble median
EQM_y ensemble median
EQM_m ensemble median


Southeast Atlantic - gauge station 83442
Average daily rainfall (mm)
Month
Jan Feb Mar Apr May Jun Jul Aug Sep Oct Nov Dec
raw ensemble median
LS_y ensemble median
LS_m ensemble median
EQM_y ensemble median
EQM_m ensemble median
obs


Southeast Atlantic - gauge station 83442
F(x)
Daily precipitation (mm)
obs
raw ensemble median
LS_y ensemble median
LS_m ensemble median
EQM_y ensemble median
EQM_m ensemble median

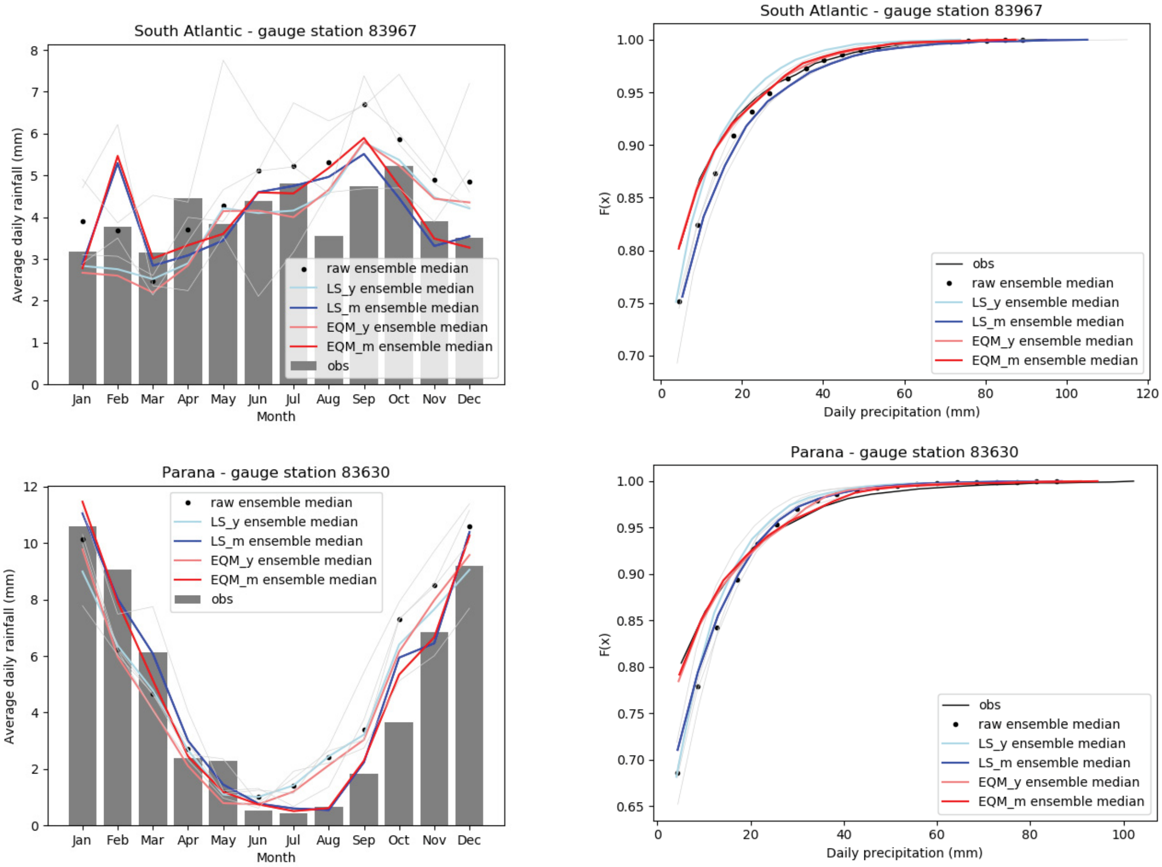


Figure S2. Long-term monthly precipitation (a) and Cumulative Distribution Function (b) in validation (1997 – 2005) of observed (obs), raw and bias-corrected by Linear Scaling (LS) and Empirical Quantile Mapping (EQM) (using yearly:_y and monthly: _m correction factors) ensemble median of all the Eta Regional Climate Models (Eta-HadGEM2-ES, Eta-MIROC5, Eta-CanESM2 and Eta-BESM), as well as individual raw climate model simulations in light-grey lines.

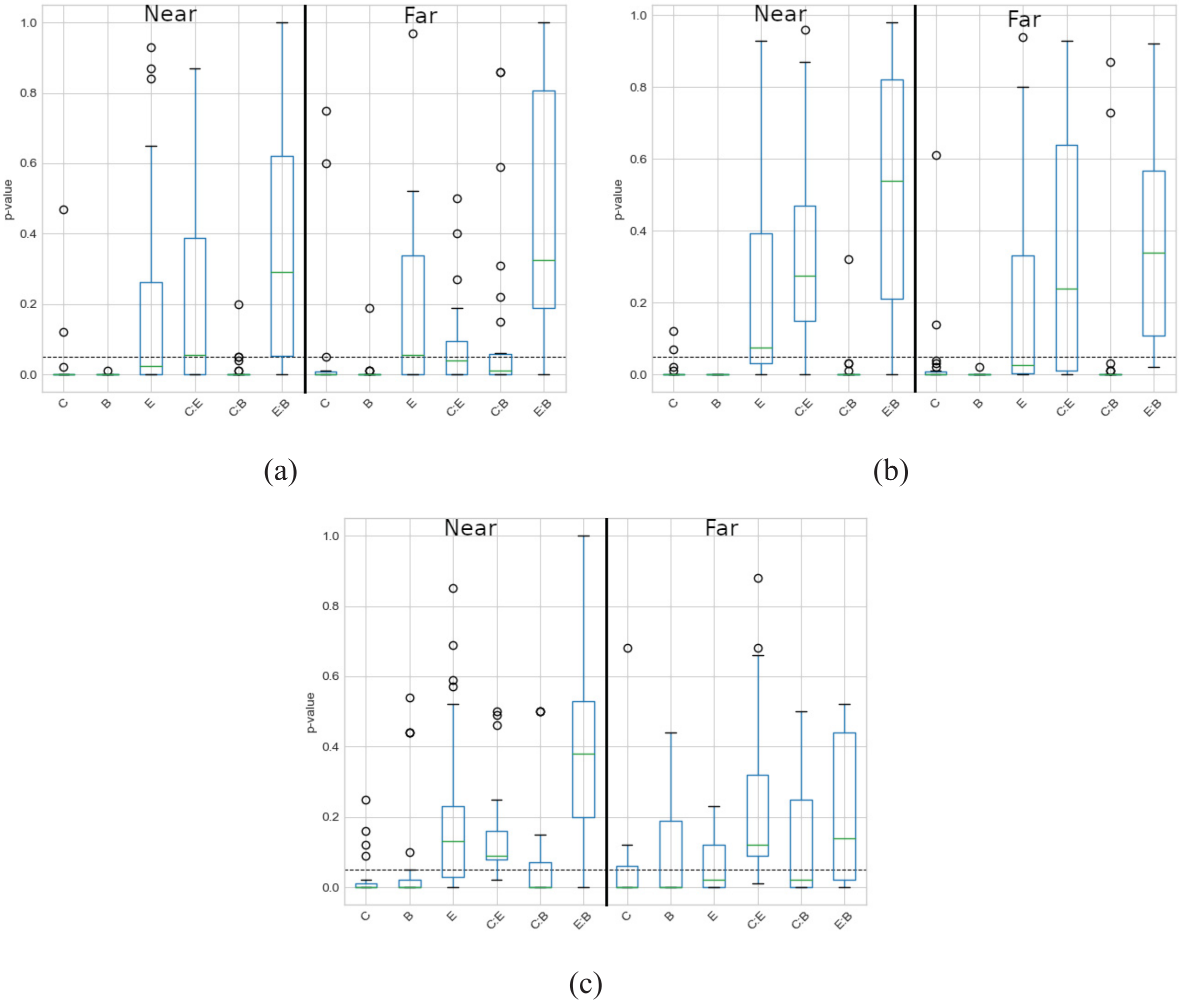


Figure S3. Significance of the ANOVA model elements in the near (2041 – 2070) and far (2070 – 2099) future for the (a) daily, (b) high and (c) low precipitation. The boxplots summarize the p-values of the F-test of the 26 gauge stations under analysis and the horizontal dashed line illustrates the test significance level of 0.05. A p-value smaller or equal the significance level indicated that the factor and/or interaction uncertainty contribution was significant for the projected precipitation uncertainty. C: Climate Model, B: Bias Correction, E: Emission Scenario, C:E, C:B, C:E the interactions between the respective sources.

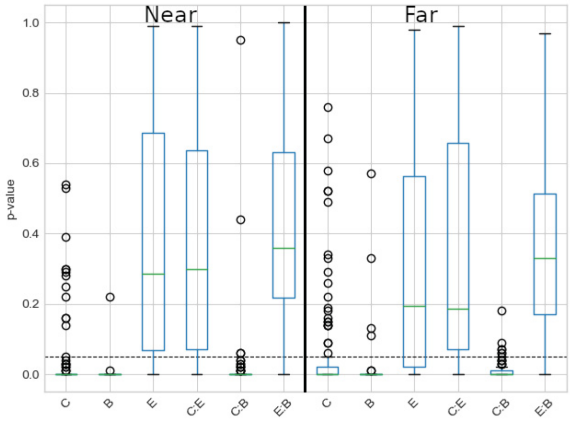


Figure S4. Significance of the ANOVA model elements in the near (2041 – 2070) and far (2070 – 2099) future for the monthly rainfall. The boxplots summarize the p-values of the F-test of the 26 gauge stations under analysis and the horizontal dashed line illustrates the test significance level of 0.05. A p-value smaller or equal the significance level indicated that the factor and/or interaction uncertainty contribution was significant for the projected precipitation uncertainty. C: Climate Model, B: Bias Correction, E: Emission Scenario, C:E, C:B, C:E the interactions between the respective sources.

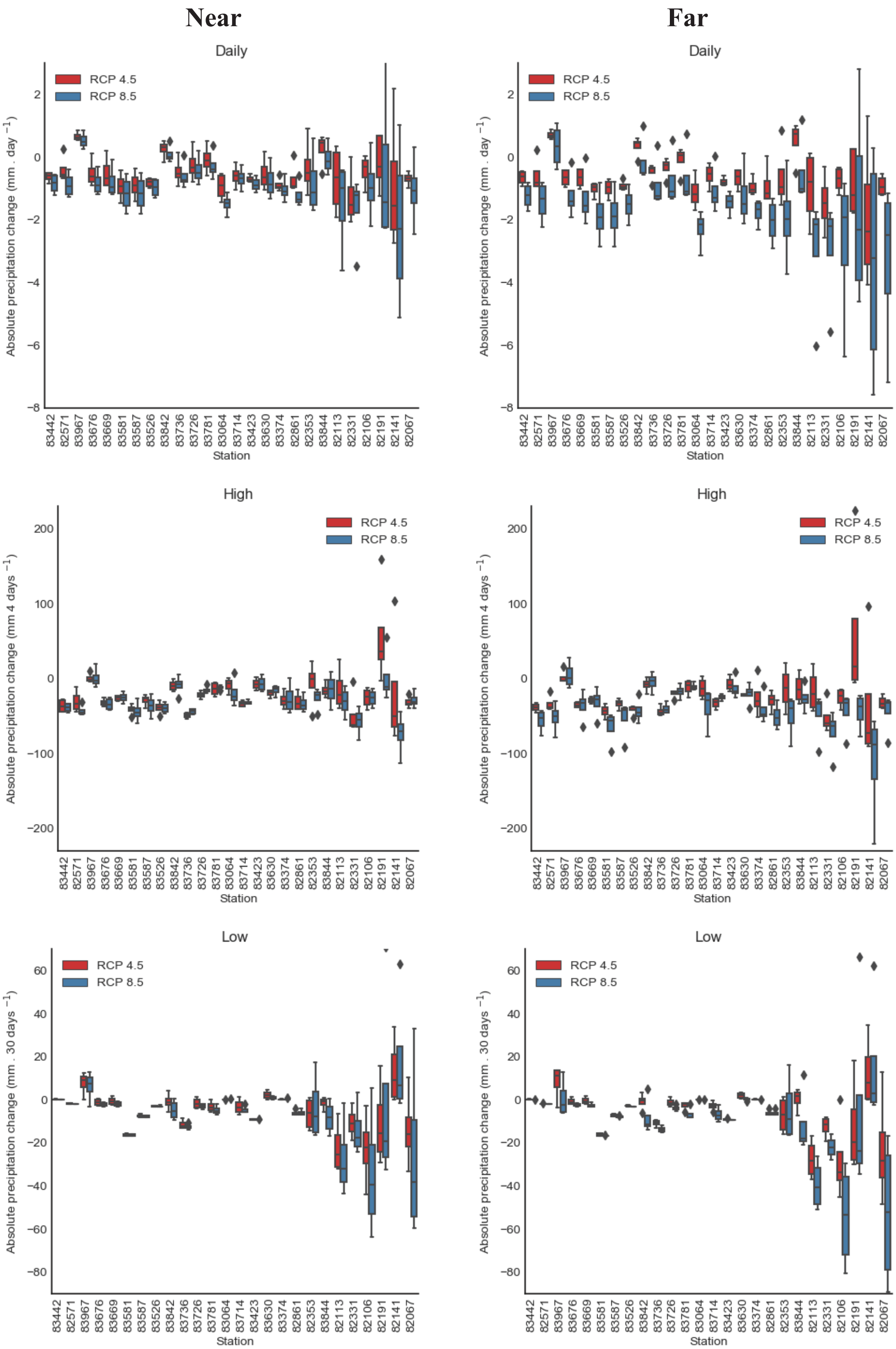


Figure S5. Absolute changes (mm) by precipitation gauge station and variable (daily – first row, high – second row and low indices – third row) for the near (left column) and far future (right column). The stations were sorted by average long-term annual precipitation (from the driest to the wettest).

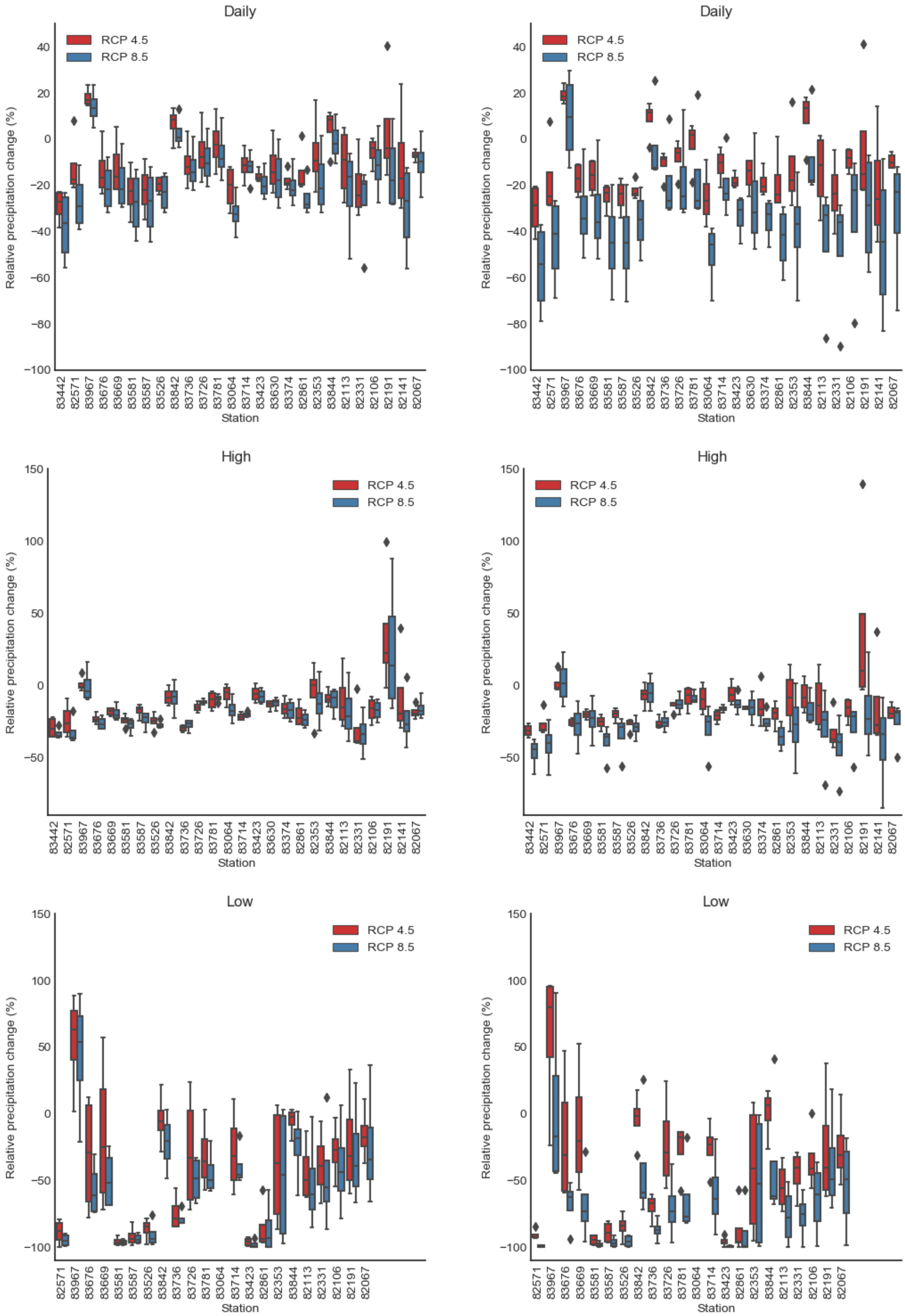
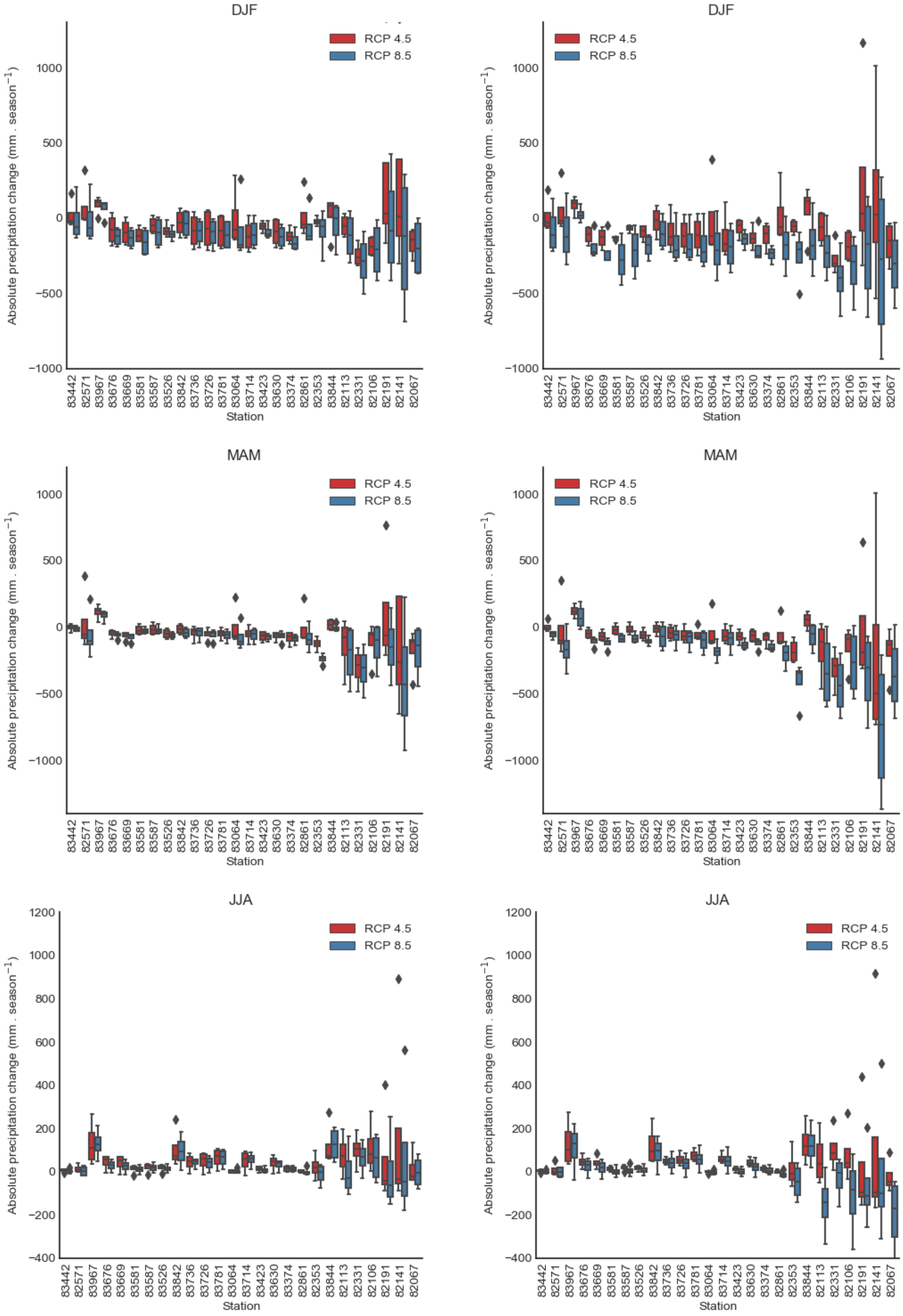


Figure S6. Relative changes (%) by precipitation gauge station and variable (daily – first row, high – second row and low indices– third row) for the near (left column) and far future (right column). The stations were sorted by average long-term annual precipitation (from the driest to the wettest).

Near **Far**


DJF
MAM
JJA
RCP 4.5
RCP 8.5
Absolute precipitation change (mm . season^{-1})
Station
83442 82571 83967 83676 83669 83581 83587 83526 83842 83736 83726 83781 83064 83714 83423 83630 83374 82861 82353 83844 82113 82331 82106 82191 82141 82067

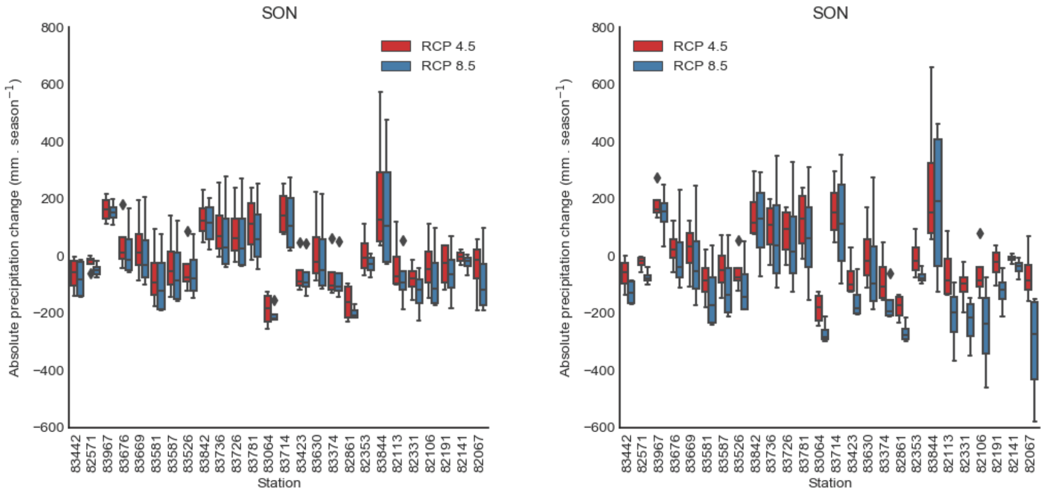
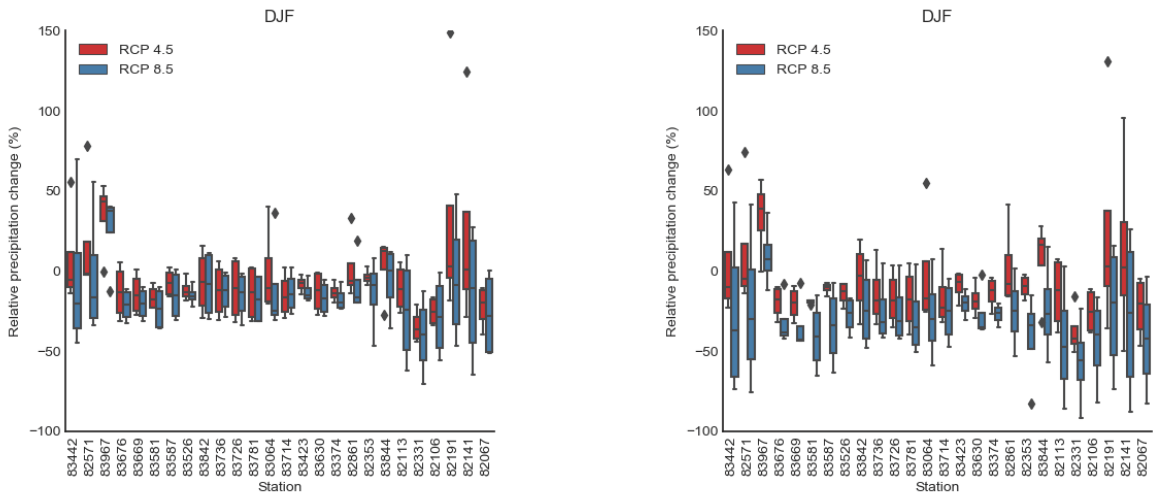


Figure S7. Seasonal absolute changes (mm) by precipitation gauge station and season for the near (left column) and far future (right column). The stations were sorted by average long-term annual precipitation (from the driest to the wettest).

Near **Far**



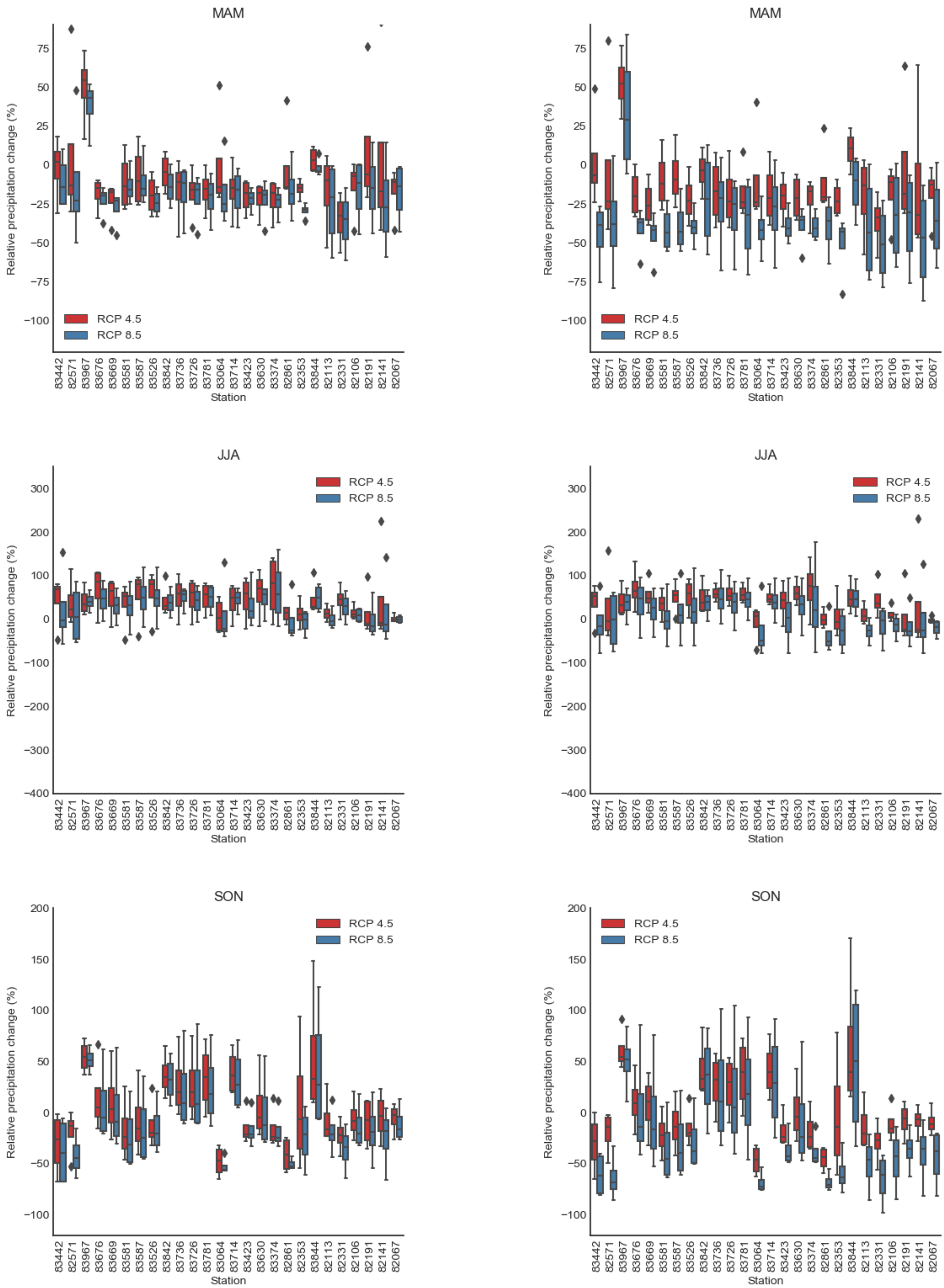
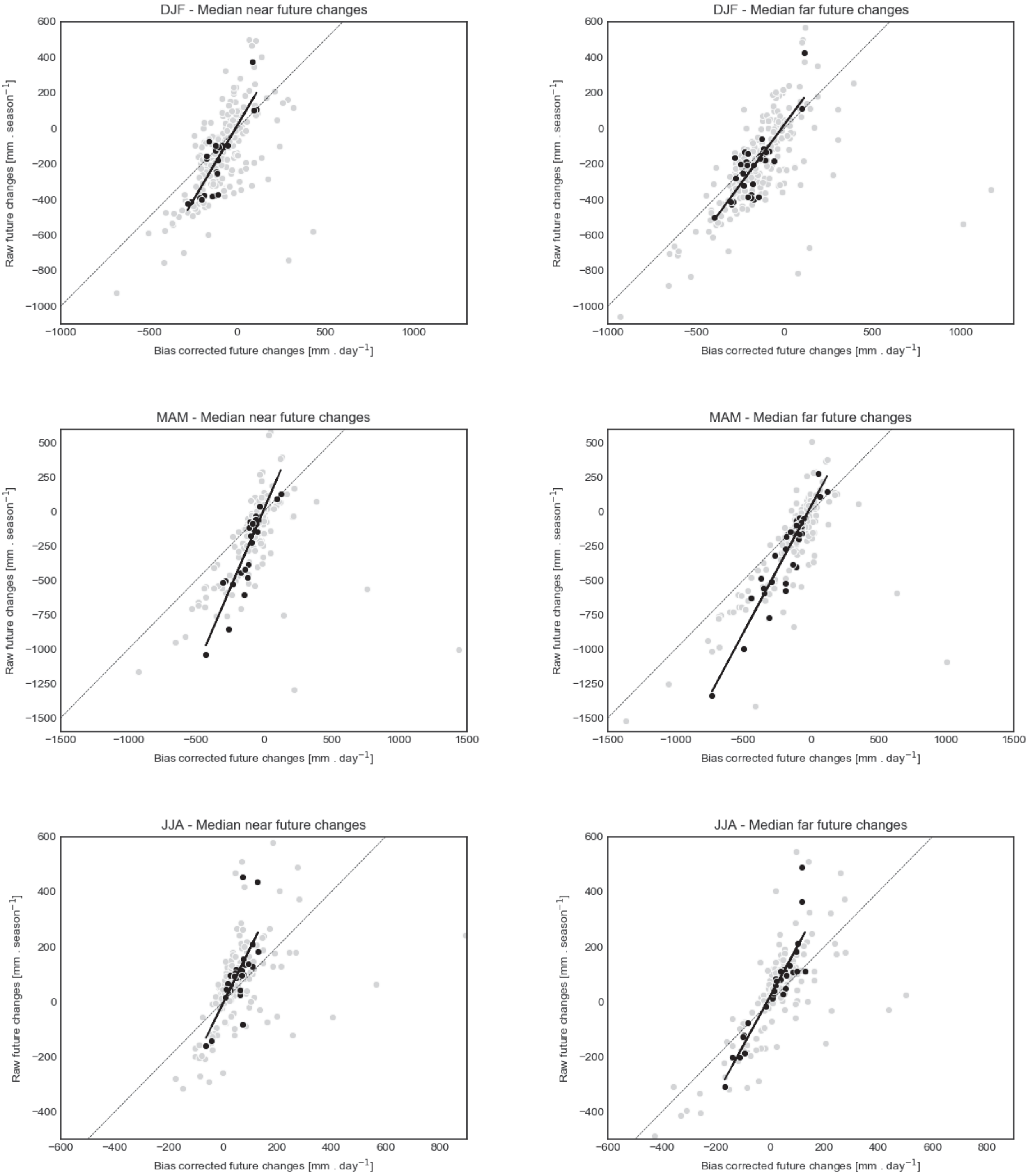


Figure S8. Seasonal relative changes (%) by precipitation gauge station and season for the near (left column) and far future (right column). The stations were sorted by average long-term annual precipitation (from the driest to the wettest).


DJF - Median near future changes
DJF - Median far future changes
MAM - Median near future changes
MAM - Median far future changes
JJA - Median near future changes
JJA - Median far future changes
Raw future changes [mm . season^{-1}]
Bias corrected future changes [mm . day^{-1}]

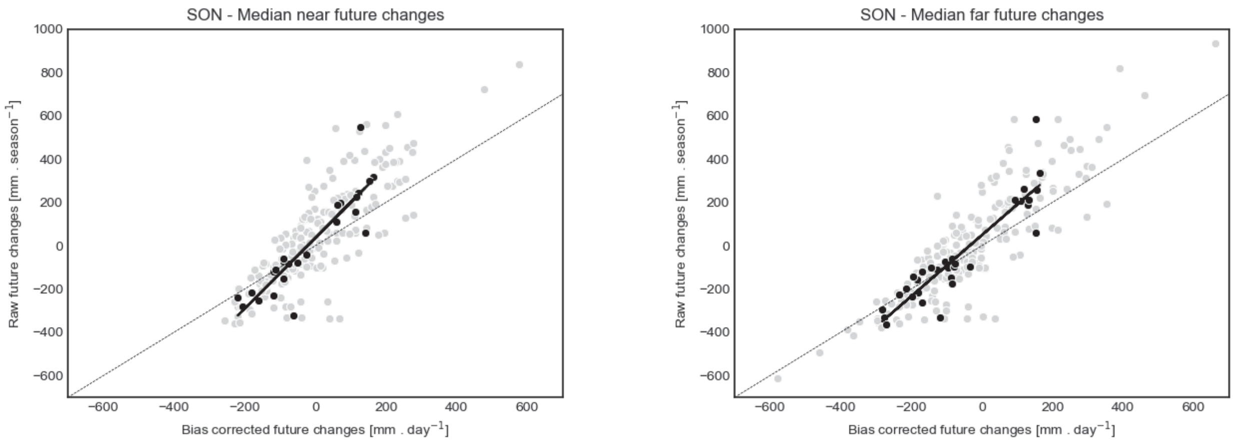
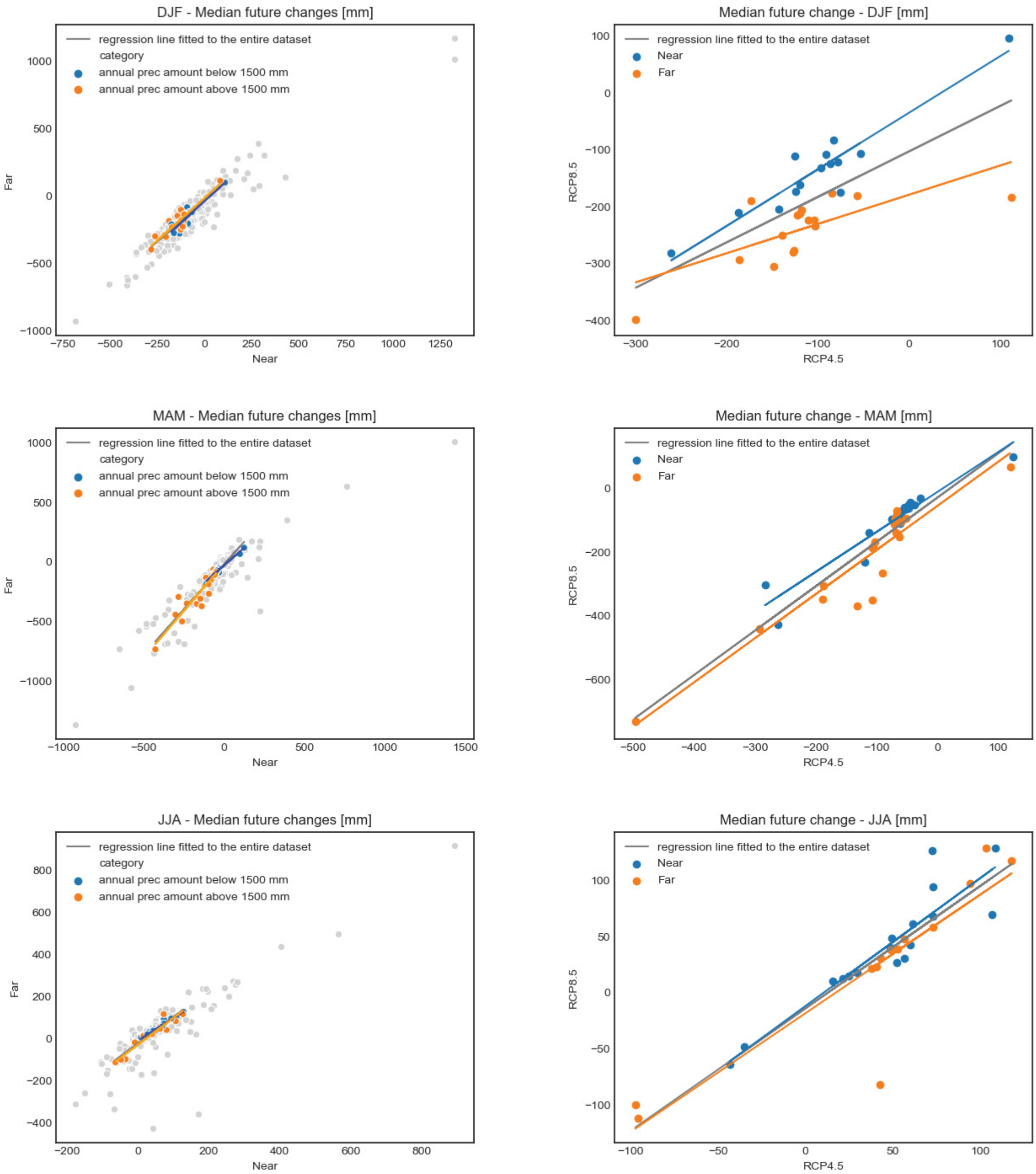


Figure S9. Scatter plot of the bias corrected future changes versus the raw future changes for the DJF (first row), MAM (second row), JJA (third row) and SON (fourth row) seasonal precipitation in the near (left column) and far (right column) future. The grey dots represent all the model's simulation, while the black dots represent the robust ensemble median.

(a) (b)


DJF - Median future changes [mm]
regression line fitted to the entire dataset
category
annual prec amount below 1500 mm
annual prec amount above 1500 mm
Far
Near
Median future change - DJF [mm]
regression line fitted to the entire dataset
Near
Far
RCP8.5
RCP4.5
MAM - Median future changes [mm]
regression line fitted to the entire dataset
category
annual prec amount below 1500 mm
annual prec amount above 1500 mm
Far
Near
Median future change - MAM [mm]
regression line fitted to the entire dataset
Near
Far
RCP8.5
RCP4.5
JJA - Median future changes [mm]
regression line fitted to the entire dataset
category
annual prec amount below 1500 mm
annual prec amount above 1500 mm
Far
Near
Median future change - JJA [mm]
regression line fitted to the entire dataset
Near
Far
RCP8.5
RCP4.5

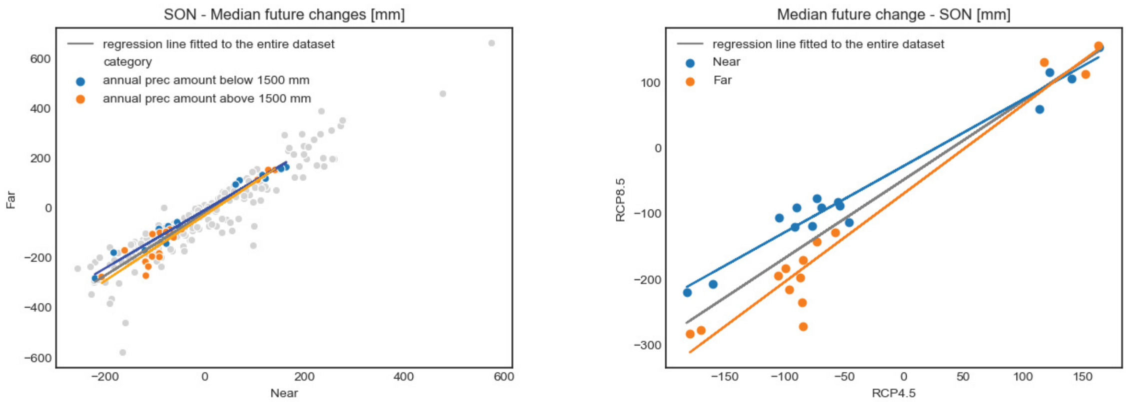


Figure S10. Correlation between near and far future (left column - a) and RCP 4.5 and RCP 8.5 scenarios (right column – b) for the seasonal precipitation.

APPENDIX C: Paper IV: Supplementary Materials

Supplementary Materials – Paper IV

Table S1. Catchment characteristics.

River	Basin	Gauge name	Gauge code	Latitude	Longitude	Mean altitude (m)	Area (km^2)	Daily mean temperature (°C)	Total Precipitation (mm year^{-1})	Mean discharge (mm d^{-1})
Piquiri	Parana	Balsa Santa Maria	64830000	-24.19	-53.75	565	20'947	21	1839	2.2
Cantu	Parana	Balsa do Cantu	64775000	-24.75	-52.70	664	2’522	20	2004	2.7
Laranjinha	Parana	Fazenda Casa Branca	64382000	-23.40	-50.45	656	2’639	21	1465	1.7
São Sepé	Atlantic Southeast	São Sepé - Montante	85623000	-30.19	-53.56	232	685	19	1528	2.2
Itajaí do Sul	Atlantic Southeast	Ituporanga	83250000	-27.40	-49.61	707	1’681	17	1550	1.9
Braço do Norte	Atlantic Southeast	Divisa de Anitápolis	84520000	-28.00	-49.12	802	376	18	1919	2.7
Forquilha or Inhanduva	Uruguay	Passo do Granzotto	72430000	-27.88	-51.75	743	1’626	18	1845	2.5
Piratini	Uruguay	Passo Santa Maria	75450000	-28.58	-54.92	272	3’233	20	1742	2.4
Piratini	Uruguay	Passo do Sarmento	75500000	-28.21	-55.32	234	5’236	26	1753	2.2
Uruguai	Uruguay	Passo São Borja	75780000	-28.62	-56.04	584	123’234	19	1843	2.4

Table S2. Ensemble estimate relative error for the long-term mean daily discharge based on the ensemble member minimum error (Min), ensemble member maximum error (Max), ensemble mean (equal weights), ensemble median and fitness-for-purpose (FFP) weighting system in Calibration.

Catchment	Min	Max	Mean	Median	FFP
64382000	0.0	0.3	0.02	0.0	0.0
64775000	0.02	1.79	0.49	0.39	0.0
64830000	0.04	1.48	0.37	0.28	0.0
72430000	0.05	0.8	0.28	0.3	0.0
75450000	0.11	1.58	0.78	0.6	0.0
75500000	0.06	1.21	0.54	0.28	0.0
75780000	0.01	0.5	0.0	0.02	0.0
83250000	0.07	0.72	0.27	0.23	0.0
84520000	0.02	1.09	0.17	0.15	0.0
85623000	0.01	0.72	0.03	0.05	0.0

Table S3. Ensemble estimate relative error for the long-term mean daily discharge based on the ensemble minimum error (Min), ensemble maximum error (Max), ensemble mean (equal weights), ensemble median and fitness-for-purpose (Fit) weighting system in Validation.

Catchment	Min	Max	Mean	Median	FFP
64382000	0.3	0.05	0.17	0.22	**0.17**
64775000	0.3	0.31	0.39	0.33	**0.23**
64830000	0.43	0.31	0.31	0.29	**0.11**
72430000	0.38	0.03	0.07	0.09	0.18
75450000	0.51	0.92	0.26	0.27	**0.09**
75500000	0.56	0.32	0.23	0.28	**0.04**
75780000	0.21	0.09	0.16	0.19	**0.16**
83250000	0.07	0.12	0.02	0.02	0.13
84520000	0.28	0.17	0.07	0.08	0.13
85623000	0.15	0.26	0.06	0.0	0.05

Table S4. Ensemble estimate relative error for the long-term annual maximum discharge based on the ensemble member minimum error (Min), ensemble member maximum error (Max), ensemble mean (equal weights), ensemble median and fitness-for-purpose (FFP) weighting system in Calibration.

Catchment	Min	Max	Mean	Median	FFP
64382000	0.13	0.56	0.38	0.4	0.0
64775000	0.32	0.65	0.5	0.51	0.0
64830000	0.03	0.71	0.48	0.56	0.0
72430000	0.53	0.8	0.69	0.7	0.0
75450000	0.0	0.66	0.26	0.24	0.0
75500000	0.02	0.81	0.36	0.36	0.0
75780000	0.02	0.54	0.38	0.4	0.0
83250000	0.02	0.67	0.39	0.41	0.0
84520000	0.24	0.54	0.43	0.45	0.0
85623000	0.09	0.5	0.34	0.35	0.0

Table S5. Ensemble estimate relative error for the long-term annual maximum discharge based on the ensemble member minimum error (Min), ensemble member maximum error (Max), ensemble mean (equal weights), ensemble median and fitness-for-purpose (FFP) weighting system in Validation.

Catchment	Min	Max	Mean	Median	FFP
64382000	0.3	0.53	0.34	0.35	**0.02**
64775000	0.45	0.56	0.42	0.43	**0.1**
64830000	0.27	0.63	0.36	0.43	**0.27**
72430000	0.66	0.64	0.58	0.56	**0.28**
75450000	0.37	1.29	0.27	0.26	**0.05**
75500000	0.07	1.37	0.3	0.31	**0.04**
75780000	0.45	0.32	0.2	0.20	0.21
83250000	0.22	0.63	0.35	0.35	**0.02**
84520000	0.21	0.58	0.43	0.44	**0.01**
85623000	0.56	0.37	0.11	0.16	0.42

Table S6. Ensemble estimate relative error for the long-term maximum cumulative deficit based on the ensemble member minimum error (Min), ensemble member maximum error (Max), ensemble mean (equal weights), ensemble median and fitness-for-purpose (FFP) weighting system in Calibration.

Catchment	Min	Max	Mean	Median	FFP
64382000	0.03	0.72	0.35	0.38	0.0
64775000	0.06	0.9	0.62	0.66	0.0
64830000	0.02	0.92	0.59	0.63	0.0
72430000	0.49	0.93	0.73	0.73	0.0
75450000	0.01	2.0	0.22	0.04	0.0
75500000	0.0	2.29	0.54	0.22	0.0
75780000	0.51	0.94	0.83	0.85	0.0
83250000	0.09	0.76	0.47	0.46	0.0
84520000	0.03	2.01	0.25	0.49	0.0
85623000	0.01	0.91	0.3	0.19	0.0

Table S7. Ensemble estimate relative error for the long-term maximum cumulative deficit based on the ensemble member minimum error (Min), ensemble member maximum error (Max), ensemble mean (equal weights), ensemble median and fitness-for-purpose (FFP) weighting system in Validation.

Catchment	Min	Max	Mean	Median	FFP
64382000	2.78	0.35	1.25	1.07	2.48
64775000	1.05	0.3	0.13	0.21	1.06
64830000	1.65	0.52	0.05	0.15	1.27
72430000	0.78	0.8	0.56	0.77	**0.45**
75450000	0.31	0.43	0.44	0.52	0.54
75500000	0.27	0.4	0.33	0.38	0.51
75780000	0.79	0.81	0.76	0.81	**0.12**
83250000	0.73	0.76	0.69	0.72	**0.00**
84520000	0.95	0.29	0.47	0.5	**0.41**
856230	0.34	0.56	0.42	0.36	**0.27**