Hydrological Modeling of Climate Change Impacts

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1 Introduction

1.1 Why Use Hydrological Modeling to Project Impacts of Climate Change?

The impacts of anthropogenic climate change on the water cycle are already apparent [1–3]. These impacts include changes in annual river streamflow [4], shifts in both flood peak magnitude and timing [5], alterations in flow duration curves [6], and changes in magnitude of low-flow periods [7]. The continued increase of global temperatures will lead to further changes in regional hydrology within the next decades through shifts in precipitation trends, melting of glaciers and permafrost [8], and a growing rain-to-snow ratio in cold regions [3, 9]. In addition, changes in natural vegetation cover, land use practices, crop water requirements, prolonged growing seasons, and soil functions may further alter the hydrological cycle [10]. Extreme events such as river flooding pose a potential threat to human societies and are likely to occur more often [2, 11]. Given that these changes directly affect agriculture, forestry, energy production, drinking water supply, sanitation, and ecosystems, there are likely to be substantial consequences for societies in many regions around the world [12]. Reliable information on potential changes to future hydrological conditions is fundamental for deciding on long-term management strategies and adaptation measures [13].

Given the impact of climate change on hydrology, hydrologists are asked to provide the hydrological basis for future water development and management, which requires an understanding of the impact of climatic and environmental change on future hydrological conditions [13]. Computer models are suitable tools to obtain such quantitative information for possible future conditions. However, any model is a simplification of reality and model simulations are uncertain, especially when a combination of models is used to represent the climate and land-surface processes, as is the case in hydrological climate change impact studies. Therefore, addressing uncertainties is an important aspect of carrying out a hydrological climate change impact study.

1.2 Goals of the Article

This article provides relevant information to understand (i) hydrological climate change impact research, (ii) the steps to perform an impact study, and (iii) the main challenges encountered in an impact study and how they can be addressed. Hydrological climate change research is an active field of research and although much progress has been made, many challenges remain. Sometimes, these challenges are difficult to overcome and being aware of the limitations is the best one can achieve. This article does not aim to provide a complete review of all models, datasets, and methods used for hydrological climate change impact studies. Rather, we summarize the most relevant subcomponents of hydrological climate change research. Uncertainties are a main focus throughout the article and best practices to characterize them are discussed. Supplementary material includes a guide to perform some key tasks leading to the production of hydrological projections, and a basis for course material to teach the analysis of climate impacts on water resources (see Section 5.6). The materials presented here presume a working knowledge of climate and hydrological sciences,

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corresponding to approximately a bachelor's degree in, for instance, geosciences. This article was written as an introduction for researchers and students who are planning their own hydrological climate change impact assessment study. However, this article can also be used to guide experienced scientists through aspects of the modeling chain with which they are less familiar.

This article is structured into seven sections. Following the introduction, Section 2 describes the basics of the model chain as a whole, providing an overview of the standard model chain used to produce hydrological projections. Section 3 provides background information on each step of the model chain and its associated uncertainties. In Section 4 uncertainty sampling and decomposition are discussed. Section 5 provides practical guidance on how to design and carry out an impact study and introduces best practices on how to evaluate streamflow projections. Section 6 contains an overview of research questions currently addressed in the literature and makes the reader aware of limitations of the approaches presented in the previous sections. In Section 7, a general outlook of hydrological climate change impact research is provided. Important terms are explained as they appear in the text; for a glossary, please see for instance the Annex III within the Intergovernmental Panel on Climate Change's (IPCC) Working Group I Fifth Assessment Report (IPCC [14]; available at https://www.ipcc.ch/site/assets/uploads/2018/02/WG1AR5_AnnexIII_FINAL.pdf).

2 Overview of the Modeling Chain

To investigate hydrological behavior under climate change, projections of future climate are needed, which are generated using general circulation models (GCMs, also sometimes referred to as global climate models). Over time, GCMs have been developed to include more systems besides the ocean and atmosphere, and they now include other processes such as global carbon cycle, dynamic vegetation, or atmospheric chemistry [3]. These models now go beyond the original definition of GCM and are thus referred to as earth system models (ESM). Owing to the evolving nature of these models, there is some ambiguity amongst these terms in climate science literature. In most cases in this article, when we are referring to GCMs, we are actually discussing ESMs. However, to keep consistent with the climate modeling community, we will use the acronym GCM.

For projections of future climate, a wide range of potential scenarios is available (Figure 1), including for example greenhouse gas emission scenarios based on specific socioeconomic assumptions or so-called representative concentration pathway scenarios based on forcing projections that could, in theory, be realized with more than one socioeconomic scenario.

Because of the coarse spatial resolution of GCMs (horizontal grid spacing~100–300 km), modelers usually downscale their output to a finer resolution, using a regional climate model (RCM) or using statistical techniques. Yet, the downscaled data can still show

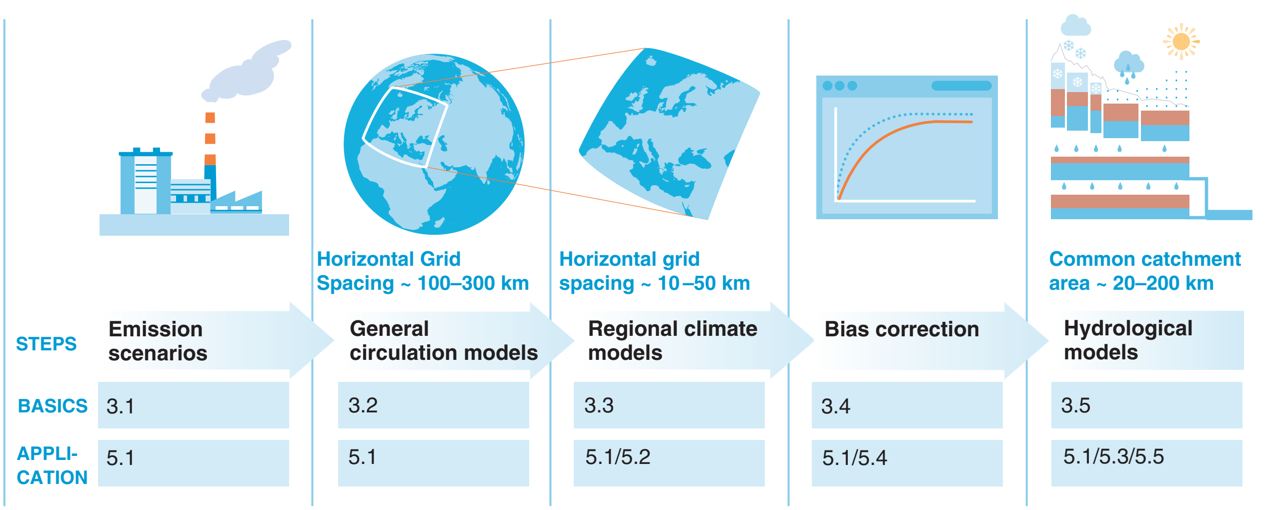

Figure 1 Schematic of a typical model chain used for the assessment of climate change impacts on streamflow. Graphics of the modeling chain are shown in the first row with the names of the steps listed in the second row. The last two rows refer to the sections of this article in which each step is discussed.

considerable biases compared to observed data [15]. Various post-processing methods (often referred to as "bias correction") have been developed to reduce biases in simulated time series. When climate model simulations are used as input to hydrological models, such bias correction generally leads to improved discharge simulations [16]. Therefore, climate projections are typically bias corrected before being used as input to hydrological models to create projections of streamflow under the influence of different climate scenarios (Figure 1). The calibration of the hydrological model (usually using observational meteorological and hydrological data) is performed in order to tune the parameters of the hydrological model so that the differences between simulated and observed discharge are minimized. These optimized parameter sets are then used in the simulations where climate projections force the hydrological model. Subsequent analysis of the projected streamflow and communication of results then follow (Figure 1).

Although hydrological models are ordinarily used to generate streamflow time series, simulated discharge can also be retrieved directly from climate models. The newest generation of GCMs include detailed descriptions of the land surface (via a coupled land surface model), which make use of river routing schemes and methods (see Figure 1 within Shaad [17]). Many different river routing schemes are now available (for a review see Clark et al. [18]). Given these advancements, and depending on the catchment size, it may make sense to consider the direct hydrological changes within the GCM or RCM output. For instance Hagemann et al. [19] compared hydrological simulations from five reanalysis driven (i.e. a global historical data set describing the state of the Earth system created by combining observations with a numerical model [20]) RCMs over two large European catchments with areas of 1.8 million km^2 and 800 000 km^2. Depending on the catchment, their results showed that generally one to two of the five RCMs were capable of simulating the annual discharge cycle fairly well, however, biases were evident in all RCM derived discharge. The authors attribute these biases to systematic errors in the model dynamics or deficiencies in the land surface parameterization. Another study by González-Zeas et al. [21] analyzed discharge output from 10 RCMs forced by GCMs for mainland Spain, which has an area of 504 782 km^2. After applying a bias correction using an "observed" global discharge dataset [22] as a benchmark, they compared the observed annual discharge cycle with that derived using raw RCM and bias-corrected discharge. Their results show that bias-corrected discharge corresponds well to observation and the raw discharge from a few RCMs reasonably captures the annual discharge cycle. Despite such applications, the catchment sizes in impact studies are often smaller than those found within the aforementioned studies and the spatial resolution of GCM and RCM hydrological output is often not appropriate. Furthermore, biases within the atmospheric forcing will be inherited by the hydrological output of a GCM or RCM. While the use of GCM or RCM hydrological output may be worth considering for particular applications [23–25], one also has to be aware that sometimes there are large deviations of GCM or RCM simulated discharge from observations [15].

The next section discusses in more detail the main steps of the typical model chain and reviews their main uncertainties.

3 Steps of the Modeling Chain and Their Uncertainty

3.1 Emission Scenarios

Emission scenarios are based on historical greenhouse gas (GHG) concentration data and provide estimates of future GHG concentration in the atmosphere, following assumptions of how emissions will change with evolving societal elements, such as demography, economic development, energy consumption, and land use. GCMs are then run with these scenarios to create projections of the climate under changing GHG concentrations.

Emission scenarios were developed by the IPCC, established in 1988 by two United Nations organizations, the World Meteorological Organization (WMO) and the United Nations Environment Programme (UNEP). So far, the IPCC has published five assessment reports. The First Assessment Report (FAR, 1990) used SA90 scenarios and the Second Assessment Report (SAR, 1995) used the IS92a to f emission scenarios. In 2000, the Special Report on Emission Scenarios (SRES) introduced the IPCC's third generation of scenarios. The SRES scenarios were used in IPCC's Third Assessment Report (TAR) and Fourth Assessment Reports (AR4). The Fifth Assessment Report (AR5) was completed in 2014 and relies on the fourth generation of emission scenarios referred to as Representative Concentration Pathways (RCPs), which are the most comprehensive attempt to characterize global emissions so far. The RCPs feature four trajectories (RCP2.6, RCP4.5, RCP6, and RP8.5), which are named after their associated anthropogenic radiative forcing for the year 2100 (+2.6, +4.5, +6.0, and +8.5 $W\ m^{-2}$). The RCP2.6 scenario is the most optimistic in that it assumes that GHG concentrations peak between 2010–2020 and then decline afterward. In contrast, RCP8.5 is the most pessimistic scenario which assumes that GHG concentrations will continue to increase throughout the twenty-first century. The Sixth Assessment Report is expected to be published in 2022.

3.1.1 Uncertainties Related to Emission Scenarios

Human component: The uncertainties in future GHG concentration are not of the same nature as those discussed in the remainder of this article. Future emissions will be determined by political and socio-economical decisions, whereas uncertainties in other elements of the model chain stem principally from our incomplete understanding of our natural environment and its imperfect representation in models. Early on, different emissions scenarios were developed to reflect the uncertainties in future emissions. Typically, the differences between the emission scenarios remain small for the first half of the twenty-first century but they can be significant in the second half of the century [3, 26].

3.2 Climate Models

GCMs are computer models, which embody simplified representations of the climate system [27]. They are essential for the understanding of the Earth's global processes under past, present, and future conditions. GCMs capture the interactions between the major components of the climate system, including the atmosphere, the oceans, the biosphere, and sea ice [28]. While simpler one- or two-dimensional models have been used to provide globally or regionally averaged estimates of climate change, GCMs are based on a three-dimensional grid covering the Earth (latitude, longitude and vertical "height"), and compute atmospheric variables (such as temperature and humidity) for each grid cell. GCMs thus, have the ability to provide both spatially and physically realistic estimates of climate change, which is the first requirement for any impact analysis. For a review of climate models of different complexity and their development over time please see Kour et al. [29].

Over the years, projections from several generations of GCMs have been produced within the framework of successive Climate Model Intercomparison Projects (CMIPs), led by the World Climate Research Program (WCRP). The goal of CMIP is to coordinate the production of GCM simulations, in order to provide consistent and reliable data, used in particular for the IPCC assessment reports. With each phase of the CMIP, model projections are further improved. Knutti et al. [30] compared CMIP5, CMIP3, and CMIP2 and found that although most models are strongly related to their predecessors, the models in the new ensemble agree more closely with observations. Model output from CMIP5 were released around 2011 and constitute the reference simulations until the release of CMIP6 simulations [31]. CMIP5 data can be downloaded through a portal provided by the Earth System Grid Federation-Center for Enabling Technologies website: http://pcmdi9.llnl.gov. A "Getting started" page is available here: https://cmip.llnl.gov/cmip5/data_getting_started.html. Note that the resolution of the GCM runs is often too coarse to realistically capture processes essential for the correct representation of streamflow generation at the local scale (such as convective events or snow accumulation in mountainous areas). Hence the majority of hydrological impact assessments do not directly use GCM simulations at their original resolution, but instead, use downscaling techniques to refine the projections.

3.2.1 Uncertainties Related to Climate Models

Model structure/parameterization: Climate models are developed by different groups across the world. These groups make different choices when deciding which processes should be represented, and how they should be represented. For instance, convection occurs at a spatial scale smaller than the grid size of GCMs, so it cannot be explicitly represented, and instead, it has to be parameterized. Different groups will use different parameterization schemes for convection, resulting in different projections of intense precipitation events. The spread among the projections of models produced by different groups reflects both limitations in our understanding of the climate system and limitations of what can be represented by climate models running at a relatively coarse resolution. To account for climate model uncertainties, it is now a standard procedure to use an ensemble of climate models, instead of a single model (see Section 4.2 for discussion of the ensemble approach to test model structural uncertainty and Section 4.3 for an ensemble approach to analyze parametric uncertainty).

Natural variability: The atmosphere is a chaotic system, meaning that a small perturbation in the initial conditions of a climate state can lead to large differences in the future [32]. This makes weather forecasting difficult and also reduces the predictability of future climate. For instance, Deser et al. [33] demonstrated the importance of natural climate variability by running the same climate model several times and only changing the initial conditions by introducing an infinitesimal perturbation. This led to very different trends in the projections. The spread in the projections reflects natural variability of the climatic system, which exists even in absence of climate change. Unlike other sources of uncertainty, natural variability has an inherently unpredictable nature and is unlikely to be reduced even as newer generations of climate models are unveiled. For an extended discussion of methods to analyze natural variability, see Section 4.4.

3.3 Downscaling

The term downscaling refers to the procedure of transferring large-scale information from GCMs to a regional or local scale, whereby the spatial resolution of the data is increased. Downscaling provides refined output at a higher spatial resolution, which is able to explicitly represent sub-grid scale heterogeneities. Consider precipitation as an example: because of the limited representation of regional topography and poor representation of mesoscale processes in GCMs, the spatial variations in precipitation intensity on regional scales often cannot be resolved. Therefore, downscaling plays a substantial role in mountainous areas, where precipitation patterns are strongly dependent on orography (Groppelli et al. [34]).

To bridge the gap between GCM output and the high-resolution climate variables required for hydrological modeling, various downscaling techniques have been developed. They can be classified into statistical downscaling (SD) and dynamical downscaling (DD). The basis for creating downscaled climate variables (e.g. temperature or precipitation) using SD is the underlying assumption that statistical relationships can be established between atmospheric processes occurring at different spatial scales [35]. These statistical relationships are used for downscaling, for instance, using weather typing schemes, transfer functions or weather generators [36]. SD is flexible and computationally cheap but is based on the assumption that the utilized statistical relationships do not change over time. Owing to the low computational cost of SD, many realizations are possible, which is for example useful when sampling uncertainties related to internal variability. DD, on the other hand, involves the use of higher-resolution (10–50 km) RCMs for limited regions (GCMs are run over the entire globe). These RCMs are run using boundary conditions provided by GCMs or reanalysis data. By using RCMs, DD offers a more physically realistic basis to downscaling when compared to SD because RCMs explicitly resolve mesoscale atmospheric processes that produce, for instance, heavy rainfall [37]. When a GCM is used to force an RCM (also called "nesting" and within this article referred to with the acronym GCM–RCM), regional detail is provided which is generally consistent with the driving GCM and also spatially coherent. For many parts of the world, climate change scenarios simulated by different RCMs are already freely available from public databases, e.g. through the CORDEX project for CMIP5 projections [38] or the ENSEMBLES project for CMIP3 projections [39]. There is no central archive for CORDEX, however, CORDEX data can be accessed from different portals, see: http://cordex.org/data-access/.

In some research papers, the terms SD and bias correction (bias correction is described in detail within Section 3.4) are used interchangeably or are instead referred to as simply "downscaling" or "statistical transformations" e.g. see the following papers which use these different terms in synonymous ways: Sunyer et al. [40], Fang et al. [41] or Gudmundsson et al. [42]. However, SD and bias correction have separate uses in some contexts, as evidenced by their motivation. The origin of SD and bias correction both date back to their use within numerical weather prediction (NWP). The first SD methods were implemented in the late 1940s [43], while bias correction developed some decades later. During the mid twentieth century NWP forecasts were too coarse to forecast weather variables at a local scale. SD models were, therefore, used to infer a statistical relationship between large-scale observational information (predictor) and an observed local variable (predictand). The statistical model was then applied to downscale the large-scale NWP forecast to the local-scale. In this circumstance, the large-scale NWP forecast is assumed to be perfectly fitted to large-scale observations. However, archived forecasts showed that the forecasts deviated heavily away from observations. Therefore, model output statistics (MOS) was introduced as a separate method from SD to correct for model biases. MOS infers a statistical relationship between a large-scale modeled predictor and an observed local-scale variable. Model biases already enter into the statistical relationship during MOS, allowing it to account for these biases. The terms MOS and bias correction are both found within current literature, where bias correction can be considered a subcategory of MOS. For further discussion of the origins of the terms bias correction, MOS, SD and their relatedness we refer the reader to Chapters 3 and 12 within the book by Maraun [44].

3.3.1 Uncertainties Related to Downscaling

Statistical downscaling: Given that statistical relationships are established between observed and climate-modeled data, uncertainties related to observational datasets will influence the effectiveness of the SD technique. Section 5.2 discusses methods to accommodate for uncertainties stemming from observational datasets. In addition, the use of SD includes the uncertainty that results from the assumption that large-scale predictors are able to capture the climate change signal. This is discussed in greater detail within Section 6.3. Numerous SD methods exist and uncertainties can be introduced depending on the method used. It is, therefore, common to use multiple methods to accommodate for these uncertainties; see Section 4 for guidance on ensemble methods. For a review of different SD methods, see for instance Fowler et al. [45] or Maraun et al. [46].

Dynamical downscaling: Although their resolution is finer, RCMs are affected by issues that also affect GCMs and by the uncertainties listed in Section 3.2 (i.e. model structure/parameterization, natural variability). This causes systematic model errors, implying that there is the need to further post-process RCM data with bias correction and to use an ensemble approach (see Section 4) when using RCM simulations as input for modeling future streamflow [47, 48].

3.4 Bias Correction

In the context of this article, a bias is defined as "the systematic difference between a modeled property of the climate system and the corresponding real property" [49]. Such properties include mean temperature or summer precipitation. Bias correction is the process of correcting climate model output to reduce the effects of systematic errors in the climate models and to make the output more suitable as driving data for hydrological models. In the case where bias correction is applied between climate model output and observational data of different resolutions, then the bias correction also inherently closes the scale gap. Whether it is reasonable to use bias correction as a downscaling measure depends on the variable being downscaled, the difference in resolution, the study location, the bias correction method, and the statistical climate aspects that could be affected [44]. Initially, biases between observed and simulated climate variables over a historical period are identified (during the so-called "control run"). These biases then serve as a basis for establishing a transformation algorithm, which is used to correct both control and scenario driven RCM runs. This implicitly assumes that the biases are invariant over time, which is not always the case [48]. Although bias correction is usually performed on RCM data output, it should be noted that a direct bias correction of GCM data is also possible and likely computationally cheaper. However, the finer RCM resolution better resolves the regional-scale variability [50], which is beneficial especially in complex topography [51].

A large number of bias correction approaches have been developed to adjust climate model simulations as reviewed by Maraun et al. [50], Teutschbein and Seibert [52] or Chen et al. [53]. They can be classified according to their degree of complexity (i.e. how many statistical moments they are able to correct), ranging from simple scaling factors to more sophisticated methods such as quantile mapping. Among the different bias correction methods, quantile mapping (also referred to in the literature as distribution mapping, probability mapping, SD and histogram equalization) has been identified as the most efficient in adjusting RCM simulations. The idea behind this approach is to match the distribution of the RCM-simulated climate values with the observed distribution with the help of transfer functions (Figure 2). This has been shown to be superior to other bias correction methods because it is able to correct quantile dependent biases including wet day frequencies and intensities. The aforementioned bias correction methods can be considered "direct methods." The delta change approach is another widely used method to correct RCM data. The delta change method is considered separate from direct methods since it uses observations as a basis and then perturbs the observed time series rather than

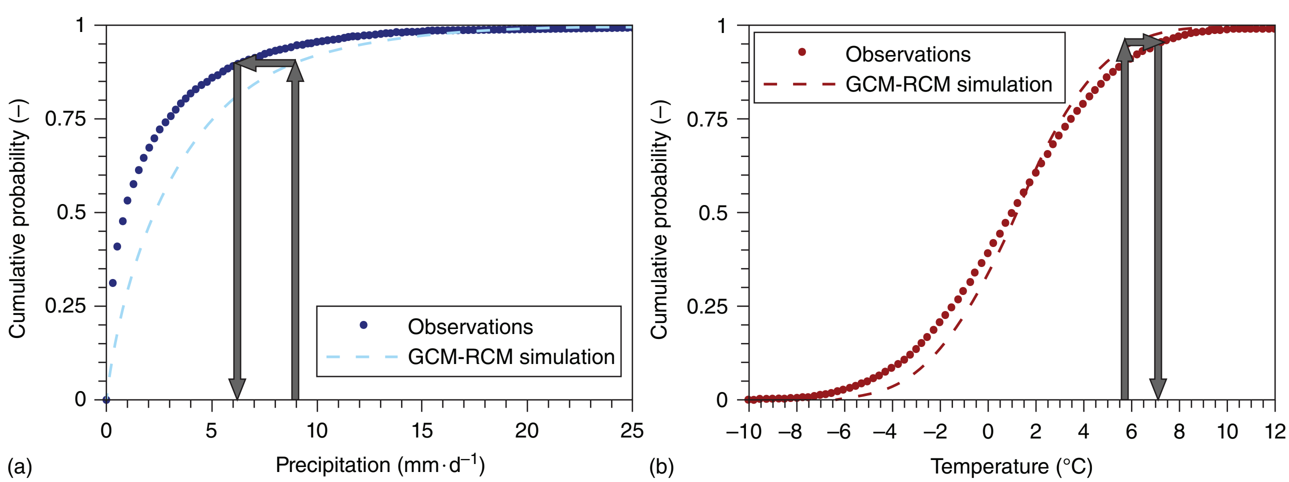

Figure 2 Illustration of quantile mapping for (a) precipitation (gamma distribution) and (b) temperature (Gaussian distribution). In both cases, the distribution fitted to GCM-RCM-simulated values (dashed line) is transformed to fit the distribution fitted to the observed data (circles).

applying a correction to modeled data. The change factors are derived from changes simulated by the climate models. The statistical characteristics of the new time series remain the same as the observed time series, which makes it a stable and robust method. However, since the projected changes (i.e. the difference between simulated future and simulated past) are simply superimposed upon the observed data, it produces future time series with dynamics similar to current conditions. This implies that the delta change approach does not account for potential future changes in climate dynamics (e.g. the number of dry vs. wet days) and that major events (e.g. heavy precipitation or hot days) will change by the same amount as all other events (e.g. drizzle or cold days), which makes the delta change approach less suitable in hydrological climate change impact studies (Teutschbein and Seibert [48]). However, due to its simplistic nature this method is still very popular in the literature and can also easily be used within a classroom for teaching purposes (see Section 5.6).

Typically, bias correction methods are univariate, i.e. they adjust only one RCM-simulated variable at a time without guaranteeing consistency in spatiotemporal fields and different climate variables [50]. Bias correction has been shown to have a moderate effect on inter-variable relationships [54]. However, this remains an understudied aspect of hydrological climate change impact studies, and the use of a multivariate method versus a univariate method may lead to different conclusions in an impact study. For instance, when temperature and precipitation are jointly corrected within glacierized catchments, this may lead to more snowfall due to more precipitation falling while temperatures are below 0 °C as compared to a univariate approach [55]. Different multivariate methods are beginning to appear in the literature, for instance, Cannon [56] introduced a method based on the N-dimensional probability density function transform, which was originally used as an image processing technique. The technique combines univariate quantile mapping and random orthogonal rotations to match the multivariate distributions of climate model data to that of observed data. Another method called Multivariate Recursive Quantile Nesting Bias Correction (MRQNBC; [57]) corrects attributes of individual variables that result in a correction of the dependence biases between different variables. The Frequency Bias Correction (FBC; [58]) method is based on the concept that the variance of the time series can be expressed as a function of frequency. The biased time series is converted into the frequency domain using the forward Fourier transform and the peaks and phases are matched with that of the observational time series. In addition, a few attempts have been made to improve the physical links between bias-corrected variables by introducing copula-based correction methods [59–61]. Copulas are used to link univariate marginal distribution functions to form a multivariate distribution function. These two-dimensional methods are, however, not yet technically mature as they either do not establish a rigorous statistical relationship between the variables or are not able to correct data at a daily timescale.

3.4.1 Uncertainties Related to Bias Correction

Symptom vs. origin: A major criticism of bias correction methods is that they only target the symptoms of model imperfections (i.e. biases in the simulations) and not the origins of these imperfections [49]. This leads to concerns about the ability of bias correction methods to correct future biases in a robust way. In a sense, bias correction provides the right answer (i.e. simulations looking like observations) but not necessarily for the right reasons. In addition, bias correction does not create subgrid variability [50] and assumes a stationarity of the bias (see Section 6.3 for further discussion). Despite these limitations, bias correction methods are still essential for hydrological impact studies, because without bias correction, systematic biases of raw climate model output would lead to substantial errors in hydrological projections.

Bias correction method: Studies have shown that the choice of bias correction method can also contribute to the total uncertainty of the modeling chain [40, 62]. For instance, Sunyer et al. [40] compared eight methods to downscale precipitation output (including four bias correction methods) from 15 RCMs from the ENSEMBLES project. Their results showed that the differences between the methods vary according to the catchments and the season being analyzed.

Observational datasets: Bias correction establishes statistical relationships between observed and modeled data. Therefore, uncertainty related to observed datasets will influence the effectiveness of the bias correction technique applied. Section 5.2 discusses methods related to the processing of observational dataset uncertainties.

3.5 Hydrological Models

Hydrological models are a simplification of real-world catchments and aim at representing the dominant hydrological processes. Hydrological models vary in their complexity ranging from purely empirical black box models to fully distributed physically based models [63]. For use in climate impact studies, bucket-type models, such as the HBV model [64, 65], are commonly used, as they are often considered to have sufficient complexity to capture the dominant hydrological processes, yet their data requirements are relatively modest. These models, also called conceptual models within the hydrological community, are based on some physical reasoning and represent catchment processes by several interconnected buckets, which mimic water storage and transfer within a landscape. These models typically represent a catchment in a lumped or semi-distributed way. In lumped models, the catchment is considered to be spatially homogeneous, while in semi-distributed models, the heterogeneity within the catchment is accounted for using subunits. For snow-dominated catchments, for instance, the division into elevation zones is crucial, as it allows the model to account for changes in temperature and precipitation with elevation. The data requirements of these models include precipitation, temperature, and evapotranspiration which are usually sufficient for discharge modeling. Another advantage of bucket-type models is that they are simple enough to be easily applied and allow, due to their smaller computational demand, a more thorough uncertainty analysis. However, there are some instances where the use of a distributed process-based model is necessary to realistically capture the variable or process of interest. For a review of applications of process-based models in hydrology, we refer the reader to Fatichi et al. [66]. When starting with the production of streamflow projections, it is advisable to use a bucket-type hydrological model. Such models are easier to setup and run than process-based models, as they have lower data requirements (this is particularly important in data-scarce regions) and their run time is lower, enabling a larger ensemble of projections. For a thorough review of the different types of hydrological models and the pros and cons of different model complexities, we refer the reader to Hrachowitz and Clark [63]. For a historical overview of the development of catchment modeling see Todini [67].

3.5.1 Uncertainties Related to Hydrological Models

Parameters: Parameter uncertainty is generally caused by (i) assumed stationarity of parameter values under changing climatic conditions and (ii) the difficulty to constrain model parameters using available data and knowledge. These two aspects of parameter uncertainty are limitations within hydrological climate change impact research and are further discussed in Sections 6.3 and 6.4, respectively.

Model structure: The response of the hydrological system to climate change can be impacted by model choice [63, 68, 69]. In practice, simpler models (i.e. lumped bucket-type models) often perform at least as well as the more complex models with regard to catchment discharge (Breuer et al. [70]), and more complexity does not guarantee that a model performs better under changed conditions [71–73]. However, this does not imply that models should not be improved; research has shown that improving process representation could increase model transferability into future conditions [74]. Yet, adding more complexity without the necessary data to support the additional scheme or parameter could lead to an increase in uncertainty along with slower run times. See Section 4.2 for a discussion of how to analyze model structure and Section 6.1 for limitations related to sampling within the hydrological model structure space.

Observational datasets: Hydrological models rely on observational data both as input to drive the simulations and for comparing the simulated time series of discharge for calibration. However, observational networks can contain uncertainty stemming from (i) instrument errors, (ii) errors in the conversion of relating measured values to the variable of interest (e.g. rating curve for discharge observations), (iii) spatial heterogeneities of the variable of interest (representativeness of the variations in the sample across space), and (iv) temporal variability of the variable of interest (whether sample variations are captured by temporal sampling) [75]. Since it is common practice to repetitively compare simulations to observation for calibration and validation purposes, issues within the observational network can lead to improper model setup and interpretation of results. Hydrological climate change impact studies rely on various observational data networks, which have different sources of uncertainty (see the earlier discussion) depending on the variable considered. For instance, although simulated discharge stemming from a calibrated hydrological model may match well with observed discharge, it is important to keep in mind that streamflow measurements during floods are uncertain. Please see Section 6.6 for a discussion of limitations related to observational dataset uncertainties.

4 Uncertainty Sampling and Decomposition

4.1 Ensemble Approach

It is now standard for studies investigating climate change impacts to rely on an ensemble approach [76]. This means that multiple runs rather than a single model run are performed and that the result is a range of possible outcomes rather than a single simulation. The various simulation runs differ in one or several aspects (e.g. different emission scenarios, climate models, climate model members, downscaling methods, bias correction methods, hydrological models, and parameter sets). Depending on computational resources and data availability, an ensemble can consist of a few (∼10) to many (1000 or more) ensemble members. The different simulation runs are then often aggregated by computing the mean or median change and the spread in the projections. The aggregation of the ensemble runs is usually a more robust estimate of future changes than if one would use one single run. Note that although both the mean and median can be used to combine ensemble runs, the median is often preferred over the mean since it is less affected by individual outliers, such as poorly performing models. The spread of the ensemble provides an estimate of the uncertainty in the projections. The following sections describe three ways to use ensembles to account for different forms of uncertainty: (i) uncertainties in the formulation of the models (structural uncertainty), (ii) uncertainties in parameter values within the models (parametric uncertainty) or (iii) uncertainty due to natural climate variability. Ensembles are also often used to isolate the contribution of other forms of uncertainty by utilizing different emission scenarios, bias correction methods, observational forcing, among other components of the modeling chain.

4.2 Ensembles to Test Structural Uncertainty

The assessment of model structural uncertainty is generally performed by using different model structures and characterizing the range of their output, known as the multi-model approach (Jiang et al. [77]; Hublart et al. [78]; Seiller et al. [79]). This method is applied in both climate and hydrological modeling. Hydrological models are developed by different modeling groups, hence their modeling philosophies and therefore structures vary (even amongst bucket-type models). Similarly, GCMs and RCMs are developed at different institutes, resulting in different representations of Earth system processes from one model to another (although often not entirely, see Section 6.2). This leads to a spread in the projections, representing model uncertainty. Figure 3 illustrates this concept for discharge projections: The spread of the projections was produced by forcing HBV using different GCM–RCMs.

4.3 Ensembles to Characterize Parametric Uncertainty

In a hydrological modeling context, the perturbed parameter approach consists of running the hydrological model multiple times using different parameter sets, generated using, for instance, Monte-Carlo procedures [80, 81], Bayesian methods [82, 83], evolutionary algorithms [84], or depth functions [85].

Within climate and hydrological modeling, the perturbed-parameter approach (also known as the perturbed physics ensembles [86]) involves the perturbation of model parameters (typically those poorly constrained by observational data) or parameterization schemes, thus creating separate simulations using each variant. This is done in order to test the model system sensitivity to the perturbations and to develop a range of equally likely model responses consistent with uncertain parameters/schemes. In the simplest form of this analysis, a single parameter is identified and the model is run. This parameter is then changed and the model is then rerun. The collection of the climate model runs as a whole is defined as an ensemble of different realizations. Typically, this approach entails the simultaneous modification of several parameters to evaluate their combined impact on the system and to estimate the range of uncertainty related to their prescribed values.

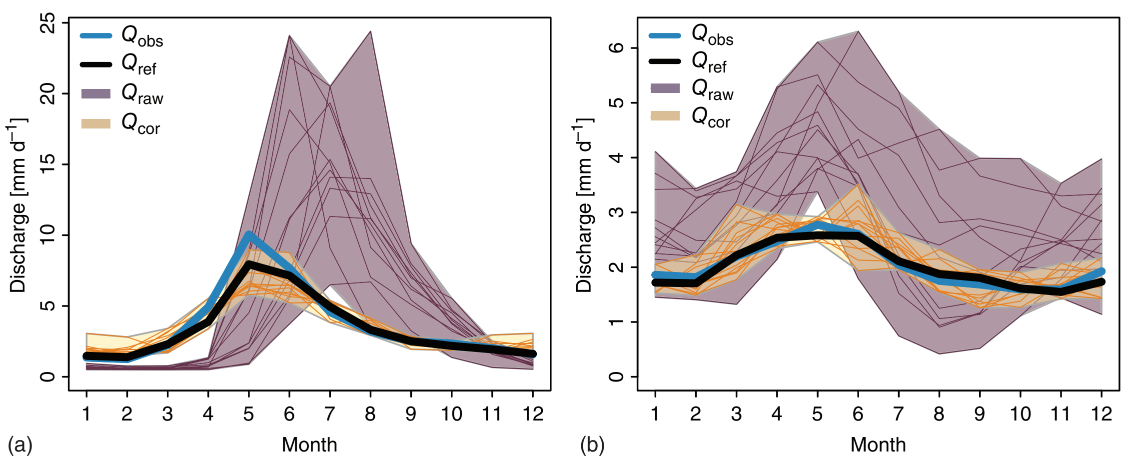

Figure 3 Seasonal discharge for the Allenbach catchment (a) and Guerbe catchment (b), both located in Switzerland, for the time period of 1980–2010. Within each figure, observed discharge (Q_{obs}) is compared to simulated discharge driven by: (1) observed atmospheric forcing (Q_{ref}), (2) raw GCM-RCM data (Q_{raw}), and (3) bias-corrected GCM-RCM data (Q_{cor}). For both Q_{raw} and Q_{cor}, the spread of the streamflow simulated using 12 GCM–RCMs from the coordinated regional climate downscaling experiment (CORDEX) is plotted (each line corresponds to one GCM-RCM, while the shading indicates the spread of the ensemble). Note how applying the bias correction reduces the spread among the members of the ensemble.

4.4 Ensemble Approach to Characterize Natural Variability

Recent studies showed that the importance of natural variability has often been underestimated when interpreting climate model projections. Initial condition ensembles involve the use of the same model and forcing but different start dates. Because of the chaotic nature of the climate system, small changes in temperature, humidity, etc. can result in highly different realizations of the system. This approach is, therefore, only applied to stochastic models or models with a stochastic setting. The chaotic nature of the atmosphere amplifies these slight differences, which results in some spread among the ensemble members. The spread provides a quantitative estimate of the natural variability of the climate system, often associated to noise.

Initial condition ensembles are utilized in a modeling setup like Deser et al. [33], who used one GCM, one emission scenario, identical initial conditions in the ocean, land and sea-ice components with different initial conditions in the atmospheric model. In this setup, the different model runs show the range of climate realities that can be achieved in the model world as a result of natural variability. Their study revealed considerable differences among the ensemble members, as a consequence of natural variability. In other words, even if models were perfect and future emissions known, the projections would still be uncertain, because of the chaotic nature of the atmosphere. A similar method was employed by Zhuan et al. [87], who used 29 different GCMs as well as a 40-member ensemble from one particular GCM. The differences among the 40 members are used to study the role of internal climate variability. The 40-member ensemble is further compared to the 29 GCM ensemble to estimate the timing of when human-induced climate change stands apart from internal climate variability. Other methodologies to analyze natural variability have also been employed, see Vidal et al. [88] and Fatichi et al. [89] who used a combination of a SD method and hydrological modeling. Natural variability represents a challenge to hydrological climate change impact studies because of its irreducible nature.

4.5 Techniques to Decompose Projection Uncertainty

The uncertainty in the projected hydrological changes can be decomposed and assigned to the different sources of uncertainty described previously. This requires a carefully developed experimental design, typically relying on the factorial combination of the different elements of the model chain (including all possible combinations of the model elements). It is a computationally demanding task, but it is necessary to isolate the contributions of each element of the model chain to the total uncertainty. Uncertainty partitioning is most commonly performed using an analysis of variance (ANOVA, Hawkins and Sutton [26]; Bosshard et al. [90]; Eisner et al. [91]). In an ANOVA framework (see Figure 4), the uncertainty is estimated from the variance among the ensemble members and the contribution of the elements of the model chain is additive. An uncertainty assessment of this kind allows for the determination of which elements of the model chain cause the most uncertainty, which helps with the design of future impact assessments. Including an additional hydrological model, for instance, might barely influence the projections, so additional runs can be avoided, which is helpful if computing resources are limited. Figure 4 shows an example of the outcome of an ANOVA decomposition where climate models are responsible for most of the spread in the projections, although there is some dependency on the variable, future period, and catchment of interest.

Studies such as Wilby [93] have suggested that the relative contribution of uncertainty from each step of the modeling chain to the final discharge projection is dependent on catchment characteristics. Addor et al. [92] produced streamflow projections for six Swiss catchments and showed that in nonglacierized catchments, uncertainty was mainly caused by GCM–RCMs. In contrast, in partially glacierized catchments, hydrological models played an equivalent role in discharge uncertainty. Bosshard et al. [90] showed that the time of year can also impact the contributions of uncertainty from different sources. They performed a variance decomposition on discharge projections and identified the GCM–RCMs to be the dominant source of uncertainty in the summer and autumn. Toward the end of the century, in winter and spring, the role of GCM–RCMs was found to diminish and instead hydrological models (as well as post-processing methods) become more important. Besides considering different catchment characteristics and the time of year, the contribution of uncertainty from the modeling chain is also dependent on which aspects of the hydrograph one evaluates. Meresa et al. [94] considered three sources of uncertainty: climate models obtained from EURO-CORDEX, hydrological model parameters achieved by calibration using observed streamflow over a reference period, and the process of fitting distribution models to extreme flow time series. The uncertainty of the hydrological parameters was estimated using the generalized likelihood uncertainty estimation (GLUE) approach. An ANOVA analysis showed that for low-flow extremes the uncertainty stemming from the hydrological parameters can be greater than the uncertainty from the climate models and distribution fitting process. For high-flow

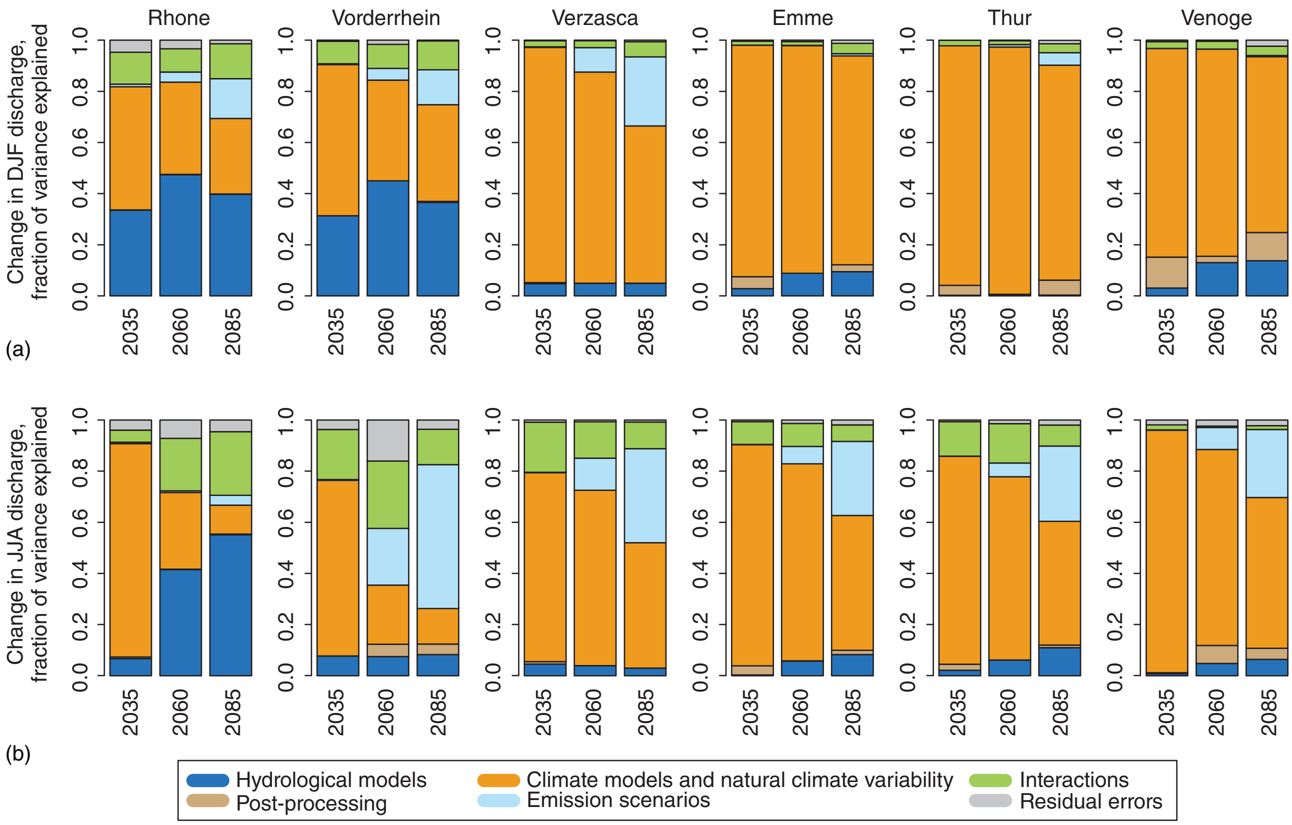

Figure 4 Decomposition of the projection variance. ANOVA partitioning among the four selected sources of uncertainty, the significant interactions, and the residual errors. Results for discharge changes in (a) winter (DJF) and (b) summer (JJA) are shown for the three 30-year future periods, centered on 2035, 2060, and 2085 for six Swiss catchments. Source: Figure provided by Addor et al. (2014) [92].

extremes, they found the climate models to be the greatest contributor to total uncertainty.

5 Application of the Modeling Chain

5.1 Design of the Modeling Chain

Modeling chains can quickly become computationally demanding, and it is beyond a single modeling study to account for all uncertainties. System sensitivity tests (changing one or a few components of the model chain and leaving the other components unchanged) are often conducted (see Section 4 on uncertainty decomposition). A key decision is which emission scenario(s), climate model(s), bias correction technique(s), and hydrological model(s) to involve. The next subsections summarize the main steps involved in the production of hydrological projections.

5.2 Collection and Processing of Observed and Modeled Data

Besides the climate model simulations, the required data for a hydrological climate change impact study typically include observed precipitation, temperature, potential evaporation, and streamflow time series.

Meteorological observational data are often available as either station data or as a gridded product, which are derived from station data using interpolation techniques [95]. Incomplete or unavailable observational data are a common concern in climate change studies, which can be somewhat overcome by advanced methods to fill in the data [96] (e.g. interpolation, hindcasting). Since both precipitation and temperature vary with elevation, values always correspond to a certain reference elevation. For station data, this is simply the elevation of the station. For gridded datasets (including RCMs), however, values correspond to the mean elevation of the grid cell. If the study area is located in a region of complex topography, such as the Alps, temperature, and precipitation values derived from a gridded product should be corrected to account for the difference of the mean elevation of the grid cell and that of the actual elevation of the study area. This is especially important for gridded data with coarse resolution such as that of RCMs. Some hydrological models can automatically account for such differences by applying an additive correction to temperature and a multiplicative correction to precipitation. Otherwise, this correction can also be performed by the modeler outside of the hydrological model. In addition, any systematic bias stemming from elevation differences is implicitly corrected through bias correction (see Section 3.4). However, it is important to note that when ranking the performance of raw RCM simulations, some of the biases within the data stem from elevation differences. When comparing raw RCM simulations, it is suggested to correct for elevation differences separately from bias correction, so that individual raw RCMs are not punished for issues related to elevation [97].

Potential evapotranspiration is not usually measured directly, but rather estimated using methods ranging from simple temperature-based equations such as Hargreaves and Blaney–Criddle (Xu and Singh [98]), to more physically based methods like the Penman–Monteith formulation [99]. Parsimonious formulations, such as temperature-based formulations, are useful in that they require less data compared to physically based formulations, but a downside of temperature equations is that they may be overly sensitive to climate change [100]. For a review on formulations used for estimating evaporation, McMahon et al. [101].

5.3 Estimation of the Hydrological Model Parameters

Parameters of a bucket-type model represent effective average values and most often cannot be linked to a specific property in the catchment that can be measured directly. Instead, calibration is used to estimate parameter values. Hydrological models are commonly calibrated against observed discharge, which means that a certain goodness-of-fit measure, such as Nash–Sutcliffe efficiency (NSE, Nash and Sutcliffe [102]) and Kling–Gupta efficiency (Gupta et al. [103]), is optimized by changing the parameter values. This can be done manually but usually automated methods are used (e.g. Monte Carlo simulations, genetic algorithms, Golberg [104]; Duan et al. [105]).

Once the model has been calibrated, it is important to test it over a period of time not used for the calibration, a step usually called validation. One particular challenge in climate impact studies is that the model is used to simulate streamflow under future climate, for which no observations are available. The assumption is often made that the same parameter values are still valid for the new situation. It is important to evaluate whether this assumption is reasonable and whether the model is "stable" under the respective change. This can be done using a differential split sample test (DSST). Using a DSST approach [106] for model evaluation is a suitable approach to explore the impacts of the assumed parameter stationarity on the simulations, i.e. to explore the transposability in time of the calibrated model. DSST relies on the calibration and validation of a hydrological model using sub-periods with contrasted climate conditions. The idea behind DSST is that the errors made by extrapolation from a time period with certain climate conditions to a time period with different conditions (both time periods using observational data so that the extrapolation errors can be quantified) can be used as a basis to determine whether the model will perform well under future climatic conditions [107]. Coron et al. [108], developed a generalized version of DSST (general split sample test: GSST), that allows for a large number of calibration-validation exercises by generating sub-periods systematically using a sliding window over the reference period. The main variables used to define the contrasted condition of sub-periods for DSST are precipitation (Vaze et al. [109]; Seiller et al. [110]; Tramblay et al. [111]; Ruelland et al. [112]), temperature (Hartmann and Bárdossy [113]), potential evapotranspiration (Coron et al. [108]), and discharge (Seibert [107]).

5.4 Evaluation and Bias Correction of the Climate Models

Until recently, subsets of GCM–RCMs have normally been chosen based on their ability to replicate current climate (temperature and precipitation metrics; Mendlik and Gobiet [114]; Wilcke and Bärring [115]). In this case, the evaluation of the GCM–RCMs and their bias correction takes place prior to hydrological modeling (Section 5.5). Recent studies such as Dalelane et al. [116] have targeted how representative the ensemble spread is by selection. Such a study is based on the notion that a climate ensemble is not fully robust because model results are not truly independent, as described in Section 6.2. The methodology first rejects poorly performing models and then selects the most independent models from the remaining ones. Besides evaluating a climate model's performance based on its ability to accurately represent climate variables, the use of hydrological metrics has recently gained more attention (e.g. high and low discharge) as evaluation criteria for the performance of GCM–RCMs and their bias correction. Streamflow can be considered an integrator of all atmospheric variables over a watershed. This approach allows for an instantaneous focus on atmospheric data with the largest influence on the simulated discharge [97]. With this approach, the evaluation of performance of GCM–RCMs and their bias correction is to be performed after hydrological modeling (Section 5.5) using hydrological metrics as standards for evaluation. It has been shown that climate model evaluation based on only a single variable/metric is not sufficient [117] and that a robust selection should rather include the evaluation of a wide variety of variables/metrics.

The selection of an appropriate bias correction method is dependent upon multiple factors. The following list summarizes the most important considerations:

1) Can the model bias be considered time invariant (should a method which alters the climate change signal be applied)? A trend preserving method is justified if the bias can be considered time-invariant and conversely a nontrend preserving method can be applied if the method can be assumed to correct the time invariance of the bias.
2) Is downscaling to a higher resolution required? If so, the downscaling should capture local variations and the response to climate change.
3) How should the bulk of the climate distribution be corrected? Consider the correction of spatial, temporal, and multivariate aspects [50].

For a deeper discussion of this topic, Chapter 12, Section 10 of the book by Maraun [44] includes background information on the points listed above and provides a decision tree for the selection and evaluation of bias correction methods (Figure 12.17). The stepwise procedures to implement a particular bias correction are highly dependent on the method employed. Teutschbein and Seibert [52] provide an overview of the steps to carry out the following bias correction methods: linear scaling, local intensity scaling, power transformation, variance scaling, distribution mapping (i.e. quantile mapping), and the delta-change approach. The authors implemented these different methods and evaluated their ability to correct GCM-RCM temperature and precipitation for five Swedish catchments. The bias-corrected GCM-RCM data was then used to force a hydrological model to create discharge simulations for present and future conditions. Their results show that quantile mapping outperforms the other methods in that it corrects the most statistical characteristics and has the narrowest variability ranges.

5.5 Force Hydrological Model with Bias-corrected Climate Simulations and Analyze Streamflow

Once the hydrological model has been run with bias-corrected GCM-RCM data using parameters from Section 5.3, the discharge projections can then be analyzed. The general approach to analyze catchment discharge is as follows:

1) Apply the hydrological model for current conditions using observed historical precipitation and temperature (PT_{obs}) as forcing data. This usually implies some form of model calibration against observed discharge (Q_{obs}). This results in a time series of simulated discharge (Q_{ref}) based on observed climate data (PT_{obs}). This step should be conducted first, in order to establish the reliability of the hydrological model.
2) Compare the observed time series for precipitation and temperature (PT_{obs}) with the raw simulations from the climate model for current conditions (PT_{raw}), also called control run. Identify any biases.
3) Use the calibrated model to simulate the discharge for current conditions using the simulated time series for precipitation and temperature from the climate model, $Q_{raw,}$ PT_{raw}. This step should be completed prior to bias correction in order to test whether the discharge is sensitive to biases in the climate model data. If biases in the climate model data are apparent in the discharge, then proceed to step 4. If biases are not apparent in both steps 2 and 3, step 4 can be skipped and references to Q_{cor} and PT_{cor} can be neglected in the following steps.
4) In most cases, biases in the climate simulations will significantly impact the streamflow simulations, making the bias correction of the raw simulations precipitation and temperature data (PT_{cor}) necessary.
5) Use the calibrated hydrological model to simulate the discharge for current conditions using the bias-corrected simulated time series for precipitation and temperature from the climate model, $Q_{cor,}$ PT_{cor}.
6) Compare the various pairs of observed and/or simulated discharge to assess different sources of error (see Figure 5 for an example of these time series):

a) Q_{obs} to Q_{ref}: biases associated with the hydrological model.
b) Q_{ref} to Q_{raw}: biases related to the climate model.
c) Q_{raw} to Q_{cor}: effect of the bias correction method.
d) Q_{ref} to Q_{cor}: performance of the model chain after bias correction.

To consider uncertainties it is recommended to perform each step multiple times (i.e. use an ensemble method) whenever possible/suitable in the steps above. In step 1 for instance, due to parameter uncertainty, it is a good practice to allow for different parameterizations, i.e. to compile an ensemble of suitable parameter sets to be used in the further analyses. Ensemble means and medians, as well as spread measures, are suitable methods to show results and uncertainties (see Section 4).

5.6 Materials Available to Get Started

The Supplementary Materials for this article are available at the website: https://www.geo.uzh.ch/en/units/h2k/Services/Encyclopedia-Climate-Change.html. When

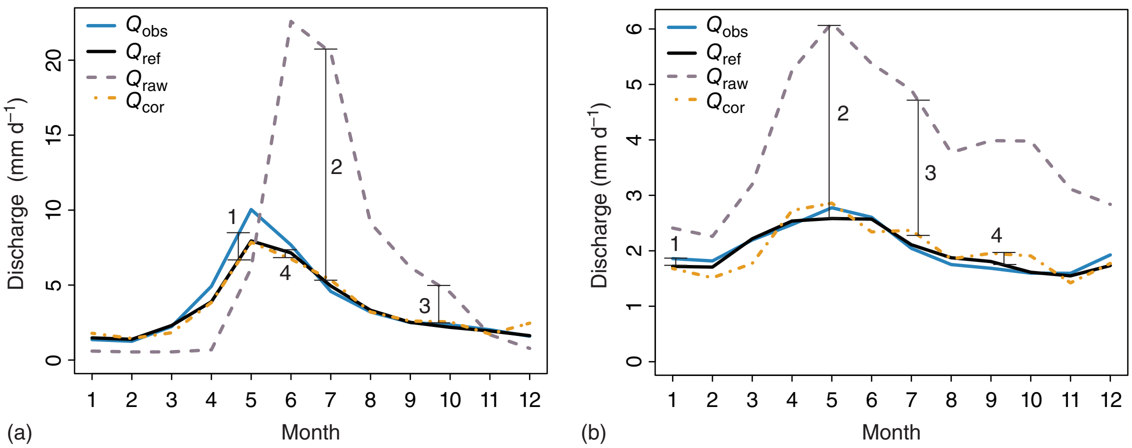

Figure 5 Seasonal hydrographs for the Allenbach catchment (a) and Guerbe catchment (b), both located in Switzerland. Within each figure, observed discharge (Q_{obs}) is compared to simulated discharge driven by: observed climate data (Q_{ref}), raw RCM data (Q_{raw}), and bias corrected RCM data (Q_{cor}). The numbered lines refer to biases described in Section 5.5, step 6, where (1) Q_{obs} to Q_{ref}: hydrological model biases, (2) Q_{ref} to Q_{raw}: climate model biases, (3) Q_{raw} to Q_{cor}: effect of the bias correction, and (4) Q_{ref} to Q_{cor}: performance of model chain after bias correction.

beginning a hydrological climate change impact assessment, a necessary step is to download GCM-RCM data and to clip the data to the area of interest. This can be a challenge for those who are new to climate change projects. A guide is provided within the Supplementary Materials which walks the reader through the steps for pre-processing GCM-RCM data in NetCDF format.

For detailed instructions on how to apply a distribution-based bias correction method, the "qmap" package in R [42, 118] provides information on the application of quantile mapping. For those new to working with a hydrological model, the hydrological model HBV (Hydrologiska Byråns Vattenbalansavdelning; Bergström [64]; Bergstrom [119]; Seibert and Vis [120]) is available for download on the Supplementary Materials website. HBV is provided as a starting point given its successful implementation in classroom settings [120]. In addition, a simplified hydrological climate change impact project (using the delta change approach) is available in the Supplementary Materials. This project has been successfully used in a master's level course in the Department of Geography at the University of Zurich in the past years. The materials can be used as a guide for self-teaching or as a starting point for faculty wishing to assign a hydrological climate change research project in a classroom setting.

5.7 Potential Mistakes

It is important to note that GCM–RCM simulations cannot be used as weather conditions for "real" days. Climate models provide one possible realization of the climate evolution during a certain time period, and while this realization should reproduce the statistics of the observations, the individual values will be different from the observation. In other words, a GCM–RCM simulation for a certain day, say 1 January 1980 cannot and should not be compared to the observation on that specific date. Instead, GCM–RCM simulations should be evaluated in a climatological sense, by comparing long-term variables, such as the mean or variability over a long period (typically 20–30 years). Similarly, computing a goodness of fit measure such as NSE using daily discharge values does not make any sense when the hydrological model is driven by climate model output. An exception to this is when the RCM is driven by re-analysis data instead of a GCM.

Another potential mistake in the quantification of climate change impacts on discharge is the direct comparison of the discharge simulations driven by GCM–RCM output for the future with that of the observed discharge or the simulated discharge using observed atmospheric forcing. Both these comparisons are not suitable to quantify the effect of the simulated climate change because differences do not only arise from a changing climate but also include model errors. The appropriate approach is to compare the simulated discharge based on climate model outputs for both current and future conditions. By keeping the driving models the same between the historical and future time periods, the effects of climate change can be more easily isolated.

6 Limitations and Challenges

6.1 Sampling Within the Hydrological Model Structure Space

Most hydrological impact studies only involve a few different model structures that represent only a small sample of the multitude of model structures currently available. This poses a problem for two reasons. First, only a small part of the model structure space is sampled, meaning the spread in the projections may not reflect the full uncertainty in the future conditions. Second, these few models differ in so many respects that it is particularly difficult to determine which differences between them contribute most to the uncertainty in the projections. A methodology to diagnose differences in hydrological model structures is to use modular modeling frameworks, such as the Framework for Understanding Structural Errors (FUSE; [121]) or the structure for unifying multiple modeling alternatives (SUMMA; [18]).

6.2 Interdependence of Climate Model Structure

A main objective of combining the output from several climate models is to produce more robust projections. Some climate models perform better than others, leaving the researcher to decide whether to give higher weight to some models. The implementation of this can often be particularly difficult in that climate model groups often share code with one another and therefore the basis for the modeled physical processes can be very similar. As Knutti et al. [122] point out, new generations of GCMs often resemble their predecessors demonstrating that much of the physics and code remains the same through generations. In such cases, model agreement does not necessarily indicate correctness. The sharing of code means that models make similar assumptions of the physical system and therefore agreement amongst the models may come from an error shared by all models, and likewise, a low spread does not necessarily mean a low uncertainty. It could instead be the result of model interdependence, i.e. models relying on the same principles, sharing code, and being tuned using the same observations [30, 123]. In the current state of the research, there is no particular best practice approach to the combination of interdependent ensemble members.

6.3 Stationarity/Instability of Model Parameters

Both bias correction and SD methods are based on the assumption of stationarity, which implies that the correction algorithm or transfer function is assumed to also be valid under future conditions. In general, a transfer function/correction is derived based on the differences between the observational data and that of the climate model output over the historical period. For the future time period, the same transfer function/correction is applied. Maraun [124] analyzed the validity of the assumption of stationarity, by using an ensemble of GCM–RCMs to simulate present and future climate. All RCMs were forced by the same GCM, which was used to represent observed large-scale boundary conditions and a particular RCM was chosen to represent regional observations. By comparing the modeled simulations to the pseudo observational data, biases were found to be generally stable and bias correction was shown to considerably improve the future climate simulations. Yet, in some regions and for some seasons, bias correction was found to increase the future bias. While this will not be the case in all situations, bias correction usually reduces the biases of the raw RCM data even in the case of nonstationarity [54]. In addition, bias correction and SD are often applied only on a single temporal resolution (usually daily values); this does not ensure that multi-day statistics, which are essential for the modeling of droughts and high flows, are correctly captured [125].

Under nonstationary conditions, such as climate change, the effects of parameter uncertainty can be expected to be considerable (Coron et al. [108]; Poulin et al. [126]; Thompson et al. [127]). While parameter values in hydrological models theoretically should reflect the physical catchment characteristics and functioning, and not climatic conditions, several studies indicate that under climate change, parameter instability is mainly due to climate dependence of the calibrated parameter values [109, 128–130]. Caution is, therefore, needed when applying parameter values to different conditions. Several studies found that transferring parameters to different climate conditions resulted in significant uncertainties especially when moving to a drier and warmer climate [108, 109, 128].

6.4 Equifinality of Parameters

Parameter uncertainty is caused by the general difficulty of identifying a single "correct" parameter set. For instance, within bucket-type models, parameter values represent effective values at the catchment scale and are usually found by calibration (or regionalization of parameter values, which have been calibrated elsewhere) and many studies have demonstrated that it is impossible to identify one single "best" parameter set. This concept, also termed equifinality [131], means that there are multiple possible parameter sets, which perform similarly for a given calibration period but might result in significantly different results when being used for particular conditions, especially if these are outside the calibration conditions [107, 132]. This provides a challenge to modelers because it implies that a certain level of understanding of hydrological processes cannot be gained through hydrological modeling as it exists today.

6.5 Climate Model Selection and Evaluation

At the time of this publication, there exists no general, all-purpose method to select and evaluate GCM–RCM combinations. Often selection is not in the control of the hydrological modeler since only some of the GCM–RCM combinations are available due to limited computing resources. A major difficulty in model selection and evaluation is the dependency on observational data as a benchmark (e.g. a model may perform well according to one observational dataset but poorly according to another). For instance, Gómez-Navarro et al. [133] and Kotlarski et al. [134] showed that the ranking of climate models differs depending on which observational datasets are used. Uncertainties in the observational dataset need to be smaller than the uncertainties stemming from the climate models so that climate models are not punished for the wrong reasons.

6.6 Accounting for Observational Uncertainties

A model, despite being firmly based on physical realism or empirically justified by performance, cannot produce accurate discharge predictions if forced with inaccurate data [135]. In many hydrological climate change impact studies, explicit consideration of observational dataset uncertainty is overlooked because it is often overshadowed by the more prominent biases and limitations associated with climate and hydrological models. It remains a major challenge for a practicing modeler to accommodate for imperfect observational data. In a practical sense, it is hardly possible to collect additional data for a particular model application. Interpolation, extrapolation, regionalization (i.e. relating information from a data-rich area to a data-poor area), and other more advanced methods are commonly used to accommodate for observational data deficiencies.

7 General Outlook

The main objectives of this article have been to introduce the topic of hydrological climate change impact modeling and to highlight how uncertainties are embedded within such research. The uncertainties discussed represent the areas within current research which have proven to be formidable roadblocks in the path to progress. Kundzewicz and Gerten [136] argue that uncertainty in projections of water resources have actually increased over time. This is due to the fact that with more information, we increasingly know more about what we do not know. Knutti and Sedláček [122] reiterate this idea by stating that uncertainties in climate change projections are not likely to be reduced quickly. Yet efforts to improve hydrological climate change impact modeling is of vital importance and progress should not be measured by how quickly model uncertainty decreases, but instead by how well we understand the processes driving climate change and its impacts.

Hydrological climate change research should be viewed with optimism. Although some uncertainties in projections may remain for the time being or cannot be reduced (e.g. natural variability), uncertainties should not prevent decisions from being made [122] nor deter those working on climate change impact research. Some of the most pressing research needs are those that may lead to more robust decisions and to a decrease in the uncertainty related to observations and projections of climate change [136]. Uncertainty can never be fully avoided and it is, thus, important to consider these uncertainties in decision making related to climate change impacts.

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