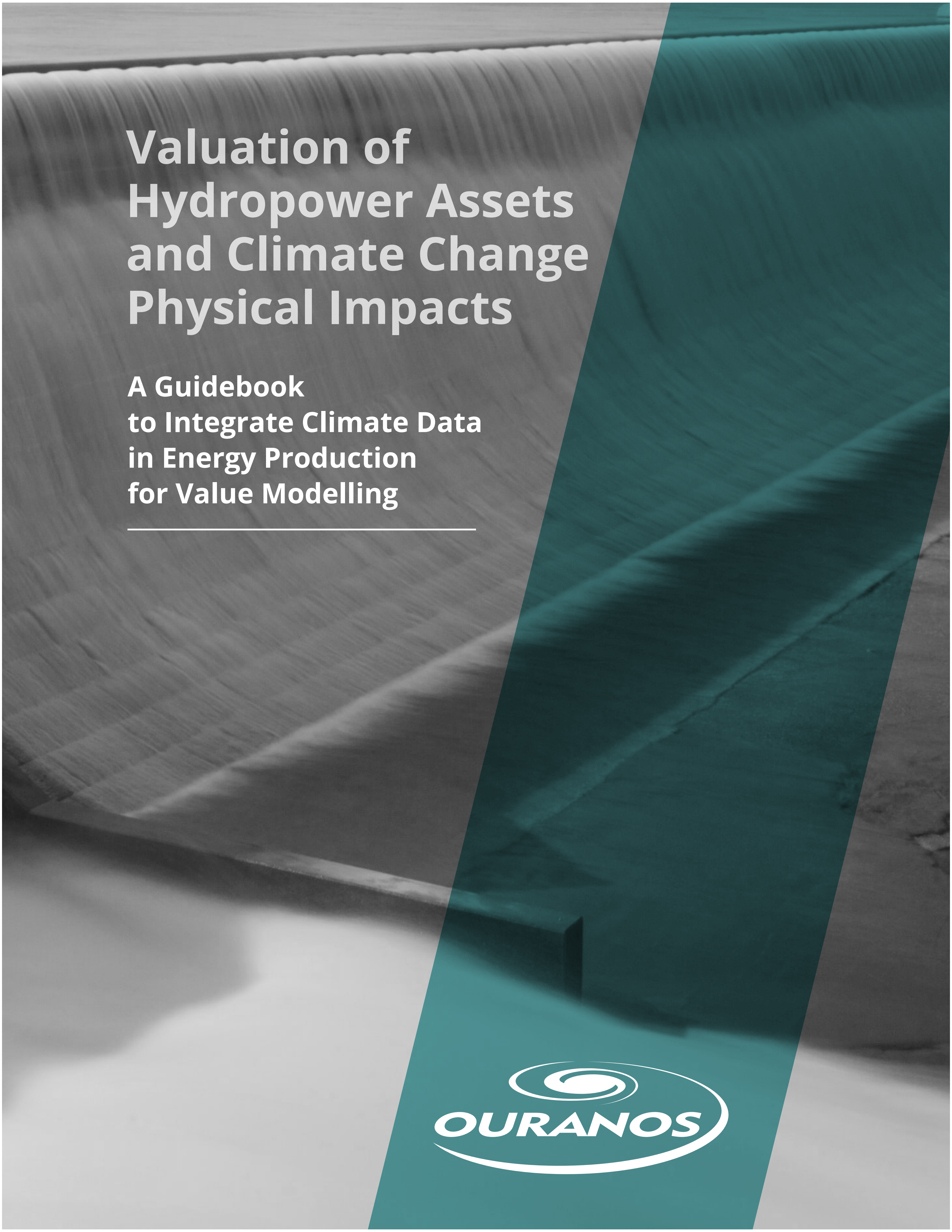


Valuation of Hydropower Assets and Climate Change Physical Impacts

A Guidebook to Integrate Climate Data in Energy Production for Value Modelling

OURANOS

Project lead

Élyse Fournier, Ouranos

Katherine Pineault, Ouranos
(now Dunsky Energy Consulting)

Authors

Élyse Fournier, Ouranos

Annabelle Lamy, Ouranos

Katherine Pineault, Ouranos
(now Dunsky Energy Consulting)

Léa Braschi, CBCL Limited

Kurt Kornelsen, Ontario Power Generation

Alexis Hannart, Ouranos (now Axionable)

Isabelle Chartier, Institut de recherche d'Hydro-Québec

Guillaume Jean Tarel, Hydro-Québec

Marie Minville, Institut de recherche d'Hydro-Québec

James Merleau, Institut de recherche d'Hydro-Québec

Collaborators

Richard Arsenault,
École de Technologie Supérieure

Bruno Benedetti,
Brookfield Renewable Power

Richard Blanchet,
Innergex Renewable Energy Inc.

Pierre-Olivier Caron-Périgny, Hydro-Québec

Kevin Sagan, Manitoba Hydro

Ali Sajid, Ontario Power Generation

Michael Vieira, Manitoba Hydro

Copy-editing

Peter McKinnon, pmck.ca

Layout Design

Pro-Actif

Suggested citation

Fournier, E., Lamy, A., Pineault, K., Braschi, L., Kornelsen, K., Hannart, A., Chartier, I., Tarel, G., Minville, M. et Merleau, J. (2020). Valuation of Hydropower Assets and Climate Change Physical Impacts – A Guidebook to Integrate Climate Data in Energy Production for Value Modelling, Ouranos, Montreal, 208 pages.

All inquiries regarding this report should be addressed to:

Fournier.Elyse@ouranos.ca

Lamy.Annabelle@ouranos.ca

October 2020

Reviewers

Richard Arsenault,
École de Technologie Supérieure

Jon Aske, CBCL

Bruno Benedetti,
Brookfield Renewable Power

Ryan Bernier, Manitoba Hydro

Richard Blanchet, Innergex

Marco Braun, Ouranos

Diane Chaumont, Ouranos

Jacinthe Clavet-Gaumont, Ouranos

Charles-Antoine Gosselin, Ouranos

David Huard, Ouranos

Nelson Jia, Brookfield Renewable Power

Jason Mahmoudi, previously at CBCL

Carolyn Mann, Natural Resources Canada

Michael Morris, Manitoba Hydro

Marcel-Paul Raymond, MPR

Gabriel Rondeau-Genesse, Ouranos

Kevin Sagan, Manitoba Hydro

Caroline Simard, Ouranos

Marie-Claude Simard, Hydro-Québec

Marc St. Laurent, Manitoba Hydro

Michael Vieira, Manitoba Hydro

Graham Waugh, CBCL

Advisory Committee

Richard Blanchet,
Innergex Renewable Energy Inc.

Thierry Bourduas,
Caisse de dépôt et placement

Jacinthe Clavet-Gaumont, Ouranos

James Falzon, European Bank for Reconstruction and Development

Chris Hayes, CEATI

David Huard, Ouranos

Kristina Koenig, Manitoba Hydro

Kurt Kornelsen, Ontario Power Generation

Kelly O'Neil, TD Canada Trust

Pierre-Olivier Pineau,
Chaire en gestion de l'énergie HEC

Marcel Paul Raymond, MPR Énergie

Odrey Robillard, Caisse de dépôt et placement (now Fonds de solidarité FTQ)

Marie-Claude Simard, Hydro-Québec

Lizzie Smith, CEATI

Richard St-Jean, Brookfield Renewable Power

Foreword

Integrating Climate Change in the Value Assessment of Hydropower Assets

By: Jacob Irving - President, Energy Council of Canada

Some aspects of the Canadian energy system are not particularly unique or exceptional. Others are quite remarkable and world leading. Canada is for example, a hands-down, global frontrunner in hydropower, which is, in fact, the country's single largest power generation source. Thanks to hydropower, Canada's overall electricity system is one of the least emitting and most renewable on earth.

Canada's unique and prominent hydropower position, however, demands persistent leadership. Canada cannot wait for other countries to address challenges and opportunities in this field. In fact, many other countries look to Canadian examples when developing their own waterpower resources.

One of the greatest difficulties facing hydropower is complacency. Those who operate hydro facilities fully understand its significant advantages. However, over time, these same advantages risk being simply assumed and then taken for granted. It is well understood within the industry how waterpower currently combats climate change and how it will be able to continue to do so well into the future. To what extent, however, might individual hydropower facilities themselves be advantaged or disadvantaged by the current and future physical disruptions climate change is bringing? How well is this fully understood?

This hands-on guide prepared by Ouranos in partnership with Canadian hydropower operators, is built on broader foundational work conducted by global organizations such as the International Hydropower Association (IHA) and the International Coalition on Large Dams (ICOLD). It will provide practical assistance to operators and relevant stakeholders, allowing them to properly value hydropower features that have, for too long, been accepted and yet somehow overlooked as invaluable. It will assist engineers, financiers, lenders, and insurers in making better hydropower decisions with greater confidence, in the face of climate change.

Finally, it is not enough anymore for hydropower advantages to be understood only by those within the industry. This Ouranos guide will go a long way toward better communicating the specific nature of hydropower capability to important, broader, and influential audiences. It might also help other energy operators and industries to begin better understanding and managing their own assets and liabilities in the face of climate change. I am pleased to be offered the opportunity to provide the Energy Council Canada's endorsement to this important, practical and worthwhile endeavor.

Acknowledgements

This study was completed with support from Natural Resources Canada through its Adaptation Platform Energy Working Group. Brookfield Renewable Power, Hydro-Québec, Innergex Renewable Energy Inc., Manitoba Hydro, Ontario Power Generation and Ouranos provided further contributions.

We thank the interviewees who helped ensure the content of the Guidebook is relevant to their organizations: Pierre Biederman (Alpage and IHA); Thierry Borduas and Michel Léveillée (Caisse de dépôt et placements du Québec); Ali Nazemi (Concordia University); Jason Shaw, Mark Stirrup, Nikou Jalayeri (Hatch); Gord McPhail, David Brown and Dave MacMillan (KGS); François Groux, Vincent Mercier, Julian Gacek, Yann Chavaillaz and Douglas Sparks (WSP).

We are also grateful to all collaborators who worked on the case studies: Nelson Jia (Brookfield); Guillaume Jean Tarel (Hydro-Québec); Richard Blanchet (Innergex Renewable Energy Inc.); Ariel Brawerman, Adam Moore, Michael Morris, Smrita Rajbhandary, Kevin Sagan, Marc St. Laurent, Michael Vieira, Zsolt Zrinyi (Manitoba Hydro); Gurmit Bhathal, Svetlana Helc, Kurt Kornelsen, Konhee Lee, Rob Priller, Connor Werstuck (Ontario Power Generation); Élyse Fournier, Annabelle Lamy (Ouranos).

Finally, we acknowledge the input and support of our colleagues at Ouranos, namely: Angelica Alberti-Dufort, Nathalie Aerens, Marco Braun, Margarita Caycedo, Isabelle Charron, Jacinthe Clavet-Gaumont, Anne Frigon, Charles-Antoine Gosselin, Patrick Grenier, David Huard, Caroline Larrivée, Dominique Lenoir, Travis Logan, Gabriel Rondeau-Genesse, Agnès Rossignol, Caroline Simard and Trevor Smith.

Ressources naturelles Canada | Natural Resources Canada

Acronyms

CC	Climate Change
CMIP	Coupled Model Intercomparison Project
CRIDA	Climate Risk Informed Decision Analysis
DSS	Differential Split-Sample Approach
ESGF	Earth System Grid Federation
GCM	Global Climate Model
GIM	Global Impact Model
HEC-HMS	Hydrologic Engineering Center – Hydrologic Modeling System
IAMC	Integrated Assessment Modelling Consortium
ICOLD	International Commission on Large Dams
IFRS	International Financial Reporting Standards
IHA	International Hydropower Association
IPCC	Intergovernmental Panel on Climate Change
ISIMIP	Inter-Sectoral Impact Model Intercomparison Project
NPV	Net Present Value
RCM	Regional Climate Model
RCP	Representative Concentration Pathway
RMSE	Root Mean Square Error
NSE	Nash-Sutcliffe model efficiency coefficient
TCFD	Task Force on Climate-related Financial Disclosures
USGS	United Sates Geological Survey

Table of Contents

List of Figures

List of Tables

Introduction

Context

Hydropower asset owners and managers, as well as other stakeholders, make financial and economic decisions based on the projected value of their production assets. Amongst other factors, the value of hydropower production assets depends upon: their productivity and efficiency; environmental and regulatory constraints; operational costs; and investments needed to maintain integrity, safety and adaptability. Climate change will have an impact on many of these factors; it will not only increase air temperature around the globe, but also modify natural processes such as water availability, floods and low flows, ice and frazil production, erosion and sediment transport, landslides, forest fires, etc.

To date, many documents have addressed this subject indirectly. The International Commission on Large Dams (ICOLD) bulletin Global Climate Change, Dams, Reservoirs and Related Water Resources assesses "the role of dams and reservoirs in adapting to the effects of global climate change, determine the threats, and potential opportunities, posed by global climate change to existing dams and reservoirs, and then recommend measures to mitigate against or adapt to the effects of global climate change" and describes "different methods and approaches allowing dam and reservoir owners to analyse potential impacts of climate change on their water resources systems" (ICOLD, 2016).

The Hydropower Sector Climate Resilience Guide of the International Hydropower Association (IHA) "provides a practical and useful approach for identifying, assessing and managing climate risks to enhance the climate change resilience of new and existing hydropower projects" and "seeks to evolve from the default use of historical data, the assumption that hydrologic variability will remain the same over the lifetime of a project and the limited knowledge of how best to access, use and interpret climate change modelling and observed climate data" (IHA, 2019).

The Climate Risk Informed Decision Analysis (CRIDA) of the Collaborative Water Resources Planning for an Uncertain Future "provides a collaborative process for risk-informed decision making: effectively assessing, managing, and communicating risks to stakeholders and decision makers, including successfully avoided risks and residual risks that cannot be avoided, quantified, or isolated" (Mendoza et al., 2018).

To the best of our knowledge, however, until now no one has clearly established the specific links between hydropower production asset value and climate change physical impacts.

Moreover, one of the biggest concerns about climate change impacts involves how the evolution in the amount and timing of water resources will affect revenues and therefore the value of hydropower production assets. Existing literature provides insufficient guidance about incorporating climate change data into asset value, and particularly how to prioritize climate change impacts alongside other concerns in a hydroelectric organization, from the integration of renewable energy in the grid to energy security issues. The complexity and cost of this work must be balanced with its potential outcome and with the other uncertainties related to business decisions.

Objectives

This Guidebook presents guidance for integrating the physical impacts of climate change into the valuation of hydropower assets. It has two objectives:

Objective 1

Illustrate potential links between hydropower production asset valuation and climate change physical impacts.

Objective 2

Propose methods to integrate climate change data into energy production for value modelling. The methods:

- Apply to all types of business activities/decisions, hydroelectric organizations and production asset types;
- Are reliable for value projections over the next 5, 10, 20, 50 and 100 years;
- Align with the work methods of hydroelectric organizations;
- Consider organizational constraints, such as time, resources and budget.

Overview and audience

Figure 1 is an overview of the Guidebook. **Section 1** addresses Objective 1 and provides a non-technical description of potential ways to integrate climate change physical impacts into asset valuation, along with the importance of doing so. For example, teams responsible for investment portfolios that include hydropower assets could benefit from this Section.

Sections 2 through **7** respond to Objective 2; they propose methods to integrate climate change data into energy production for the purposes of value modeling. **Section 2** is intended for the hydroelectric sector in general, and presents traditional valuation method, along with a valuation method that considers climate change and its uncertainties. **Section 3** through

7 cover in greater depth the methods to value assets in light of climate change. The sections present several possible options, along with their advantages, disadvantages and specific challenges, and are intended for technical staff. For example, teams responsible for climate change adaptation, water resources management, and energy security could benefit from these sections. **Appendix J** – Case studies provides concrete applications of the methods in the hydroelectric sector by the partners of the project.

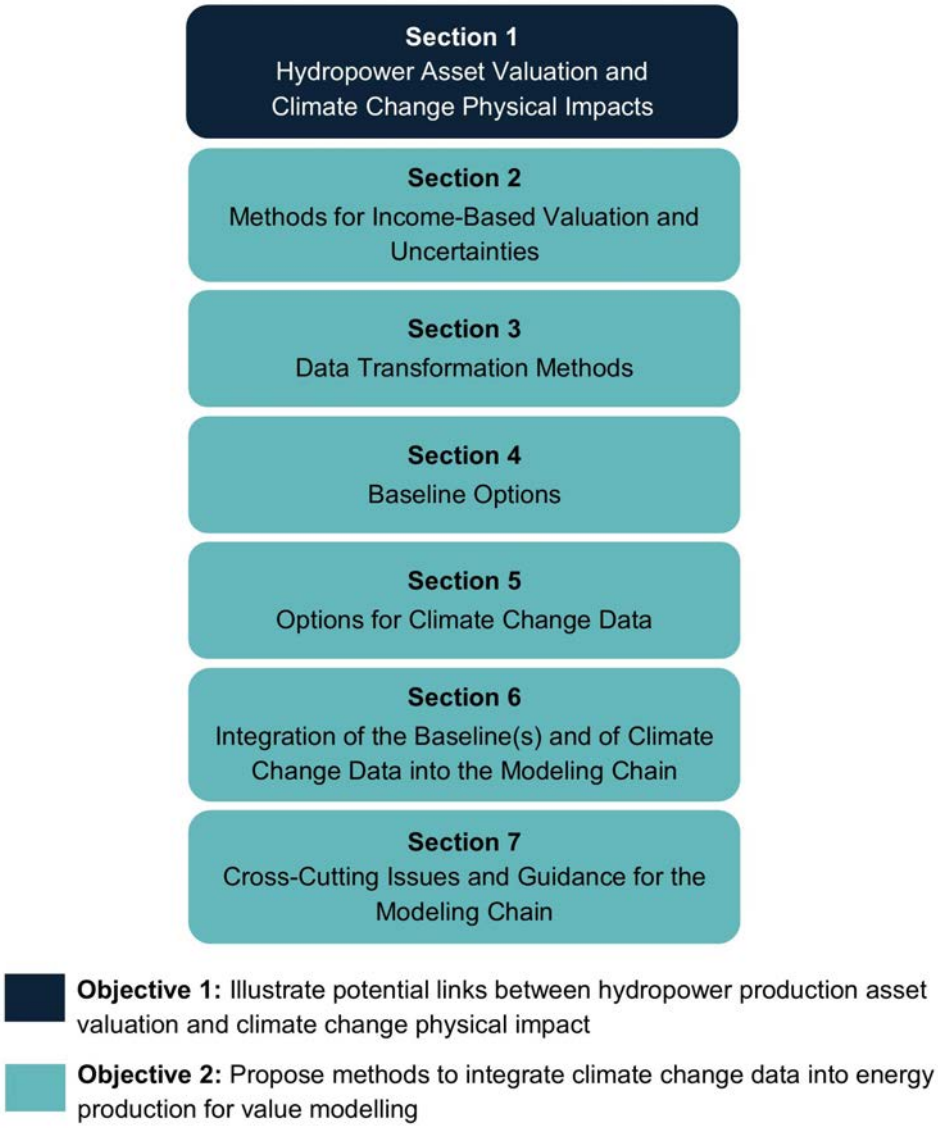


Figure 1 Overview of the Guidebook and its objectives

Scope, strengths and limitations

The integration of climate change physical impacts into the valuation of hydropower production assets is too broad and complex a subject for any single Guidebook. Moreover, an accepted standard for climate change integration has yet to emerge in the literature or in practice.

- To align with the Task Force on Climate-related Financial Disclosures (TCFD) risk categories (TCFD, 2017), the Guidebook focuses particularly on chronic physical risk and opportunities related to climate and hydrology. Transition risk (policy and legal, technology, markets and reputation) and acute physical risk (event-driven) are addressed in **Section 1** – Hydropower Asset Valuation and Climate Change Physical Impacts for screening purposes only.
- Climate change will alter multiple natural processes impacting the value of hydropower production assets. These impacts will differ by region and time period. Therefore, the Guidebook illustrates potential links between hydropower production asset valuation and climate change impacts without quantifying them (**Section 1**).
- The Guidebook demonstrates multiple ways that valuation methods can incorporate climate change impacts (**Section 1**), yet concentrates specifically on the income-based method as it is appropriate for many business activities and is already used widely in the hydroelectric industry (**Sections 2** through **7**).
- The Guidebook focuses on incorporating climate change data into the modeling chain currently used to value assets. It focuses more specifically on hydrology, as it has important impacts on asset value.
    - It leaves out the impacts of climate change on electricity costs and demand.
    - It leaves out the impacts of other natural processes on asset value.
    - It leaves out a variety of assumptions and complexities in energy and value modeling. Energy and value modeling incorporate many variables, some with significant ranges of future uncertainty.
- The Guidebook is not prescriptive; instead, it presents several options, along with their advantages, disadvantages and specific challenges. The Guidebook applies to all types of business activities and decisions in hydroelectric organizations. None of the options presented is ideal for all organizations; all the options may be adapted to an organization's particular circumstances and constraints. The use of non-prescriptive language (e.g. should instead of must) strives to respect organizational constraints.
- The Guidebook is informed by the science of climate change studies and, in some places, identifies scientific limitations. It is also informed by practice through the use

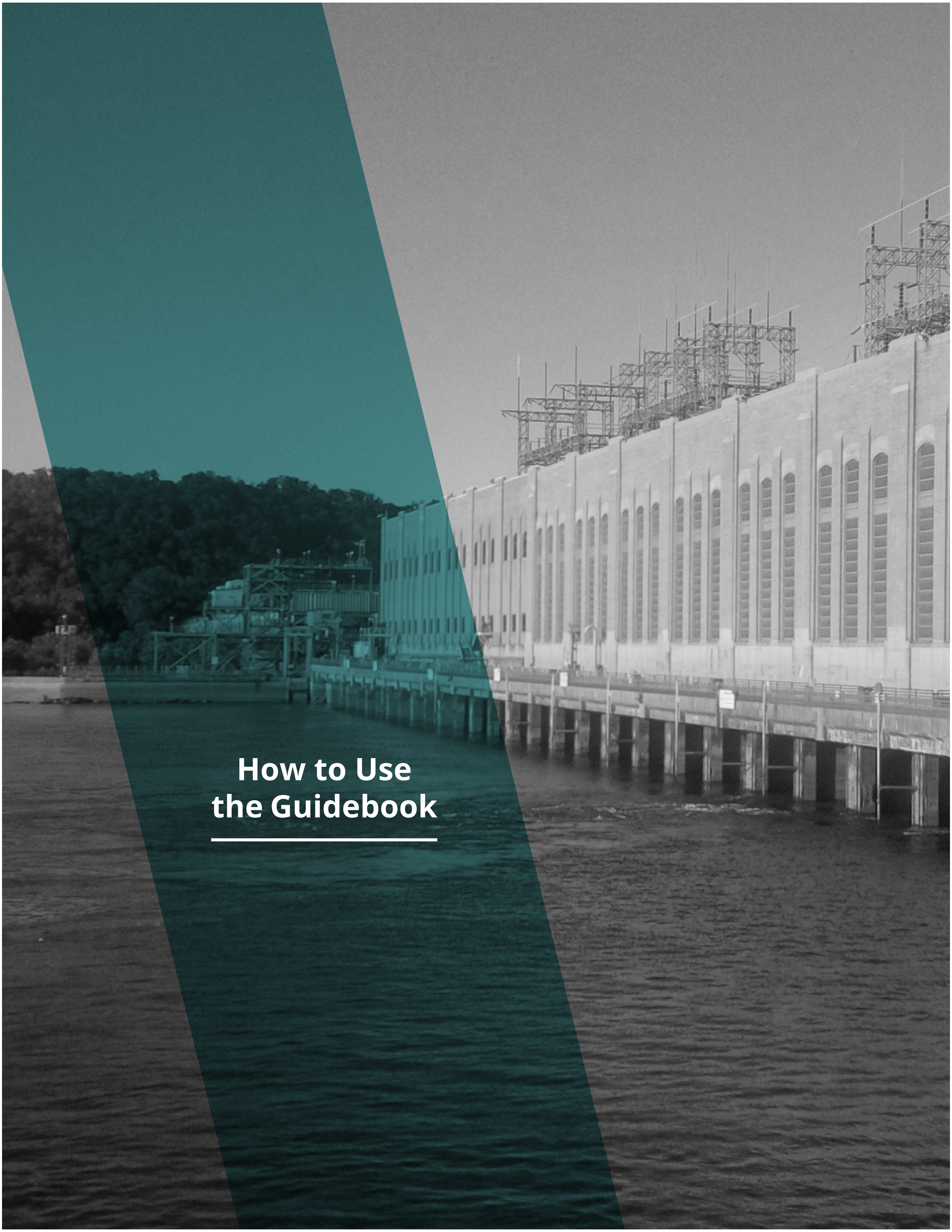
of case studies conducted alongside hydroelectric organizations, where climate data was integrated into the valuation of their assets (**Appendix J** – Case Studies).

- The Guidebook does not provide guidance on climate-informed decision-making (e.g. choosing a turbine based on future climate uncertainty). Other documents, such as the Hydropower Sector Climate Resilience Guide (IHA, 2019), the CRIDA (Mendoza et al., 2018) and the Ouranos Decision-Making Project (Ouranos, 2015) are better suited to this purpose.
- The methods to integrate climate data in hydrology for value modeling are applicable internationally, even if the examples and the resources provided herein are mostly from North America.

Methods

The Guidebook is the result of an Ouranos-led co-production involving Brookfield Renewable, Hydro-Québec, Innergex Renewable Energy Inc., Manitoba Hydro, Ontario Power Generation and École de technologie supérieure, with support and funding from Natural Resources Canada. All organizations were involved at each stage of the project, from development to dissemination of results.

A series of activities informed the production of the Guidebook. A workshop with each hydroelectric partner and phone interviews with international stakeholders were conducted to better understand their needs and constraints. Peer-reviewed publications, as well as gray literature, were consulted. Finally, a case study was developed with each hydroelectric partner to identify and test the method to integrate climate data into the valuation of its assets (see **Appendix J** – Case Studies).



How to Use the Guidebook

This section provides the practitioner with specific steps to use the Guidebook. The valuation of assets is not necessarily a straightforward and linear process, so these steps may have to be adjusted the steps to meet the practitioner's particular circumstances and constraints.

Preliminary steps before the integration of climate data in energy production for value modelling include:

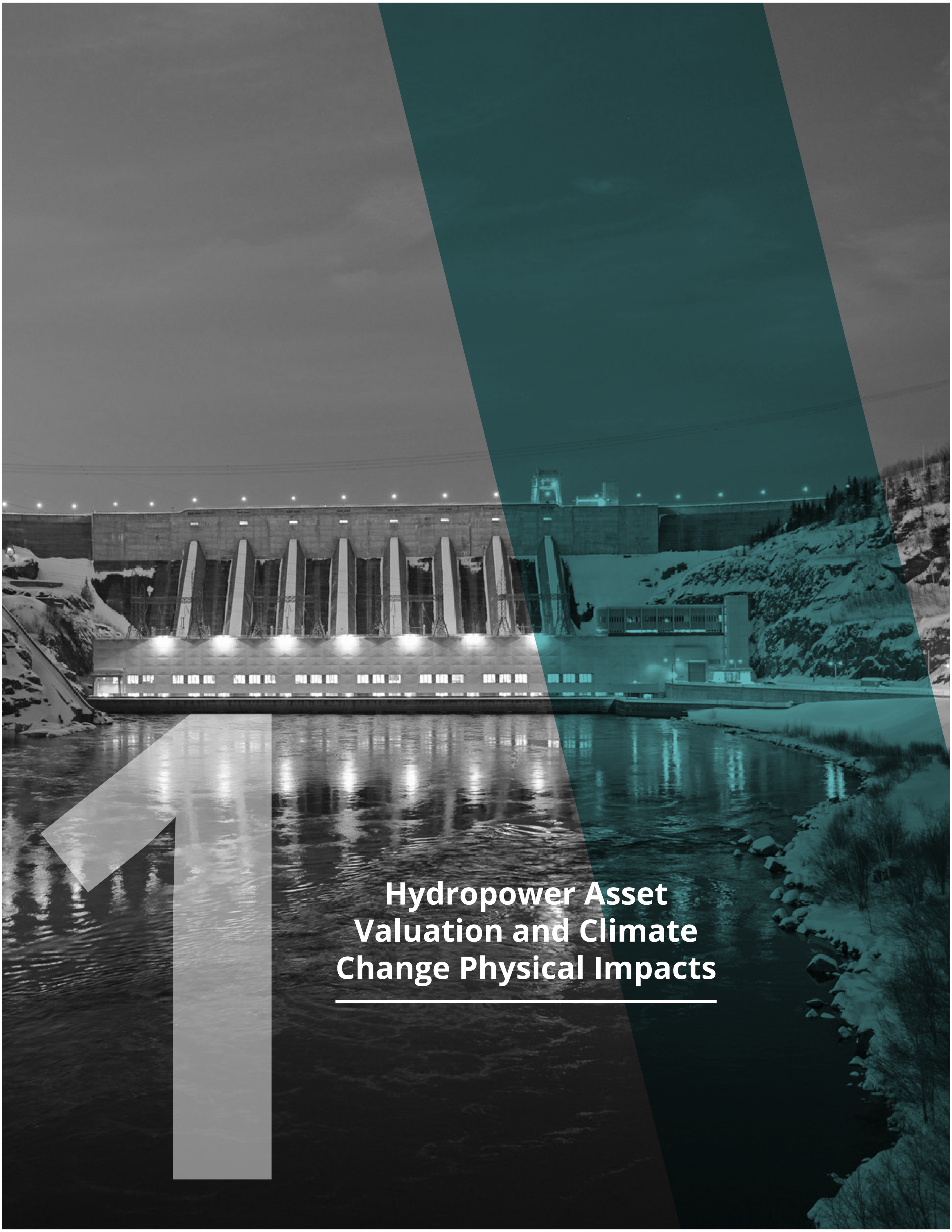
1. Define project goals and constraints (business decision, time line, budget, assessment time period, appetite for change/innovation, etc.).
2. Decide which type of value will be used for the business decision (**Section 1**).
   a. If fair value and income-based are appropriate, proceed with the next steps.
   b. If fair value and income-based are not appropriate, the Guidebook is not applicable.
3. Scan through **Sections 2** through **7** to get an overview of the process.
4. Identify members of the project team and the numerical models to be used (**Section 2**).
5. Start managing the change in organizational practices (**Section 7.1** – Managing the change in organizational practices).

Table 1 summarizes the steps proposed in the Guidebook. There are three groups of steps: Selection and development of the baseline(s) (**Section 4**); Identification and selection of climate change data (**Section 5**); and Integration of the baseline(s) and climate change data in the modeling chain (**Section 6**). **Table 1** correlates the steps with the relevant sections of the Guidebook based on the options selected (presented in the top row) for the baseline(s) and climate change data. Mandatory steps are identified with a filled dot (●) and optional steps with an empty dot (○). The results of the steps, shown in the last row of the table, are simulations based on the baseline(s) and simulations integrating climate change.

Table 1 Steps to integrate climate data in energy production for value modelling according to baseline and climate change information options

	Step #	Step	Sections / Appendices in the guide	Baseline options: Climatic and hydrologic baseline	Baseline options: Hydrologic baseline only	Climate change data options: Raw climatic simulations	Post-processed climatic simulations	Weather generators	Pre-computed results from climatic simulations	Hydrologic simulations	Global datasets and proxies	Pre-computed results from hydrologic simulations
Selection and developmement of the baseline	1.01	Select the baseline	Sect. 4	●	●							
	1.02	Make general assessment of the data	-	●	●							
	1.03	Assess adequacy of climatic baseline	App. E	○								
	1.04	Carry out detection and attribution study (if needed)=	App. B	○								
	1.05	Apply data transformation (if needed)	Sect. 6.2/6.3	○	○							
	1.06	Select and calibrate hydrologic model	App. F	●								
	1.07	Run hydrologic simulation based on climatic baseline	-	●								
	1.08	Assess adequacy of hydrologic simulation based on climatic baseline	App. G	○								
	1.09	Carry out sensitivity analysis with the modelling chain	App. H	○	○							
Identification and selection of climate change data	2.01	Identify climatic change information	Sect. 5			●	●	●	●	●	●	●
	2.02	Make sure you chose "Climatic and hydrologic baseline"	Sect. 4			●	●	●	●			
	2.03	Make sure to meet best/good practices for ensemble approach	App. I			○	○	○	○	○	○	○
	2.04	Make GCMs selection (if needed)	App. C			○						
	2.05	Evaluate transferability of data and results (if needed)	App. D				○	○	○	○		○
	2.06	Assess the adequacy of the climatic simulations	App. E				○	○				
Integration of the baseline(s) and climate change data in the modelling chain		From climatic to hydrology										
	3.01	Apply data transformation (if needed)	Sect. 6.2			○	○	○	○			
	3.02	Assess the adequacy of the climatic scenarios	App. E			○	○	○	○			
	3.03	Run hydrologic simulations with climatic scenarios	-			●	●	●	●			
		From hydrology to energy										
	3.04	Assess the adequacy of the hydrologic simulations	App. G			○	○	○	○	○	○	
	3.05	Apply data transformation (if needed)	Sect. 6.3	○		○	○	○	○	○	○	○
	3.06	Assess the adequacy of the hydrologic scenarios	App. G	○		○	○	○		○	○	
	3.07	Run energy simulations with hydrologic scenarios	-	●	●	●	●	●	●	●	●	●
		From energy to value										
	3.08	Assess the adequacy of the energy simulations	-	○	○	○	○	○	○	○	○	○
	3.09	Apply data transformation (if needed)	Sect. 6.4	○	○	○	○	○	○	○	○	○
	3.10	Assess the adequacy of the energy scenarios	-	○	○	○	○	○	○	○	○	○
	3.11	Run value simulations with energy scenarios	-	●	●	●	●	●	●	●	●	●
Result				Simulations based on baseline		Simulations integrating climatic change						

● mandatory ○ optional



1

Hydropower Asset Valuation and Climate Change Physical Impacts

Integrating climate change into the complex but essential task of valuing a hydropower asset can represent a significant challenge. To help meet this challenge, **Figure 2** illustrates the potential links between hydropower asset valuation and climate change physical impacts according to specific contexts. This section describes how to use **Figure 2** properly. **Section 1.1** describes relevant valuation contexts and assessment periods. **Section 1.2** presents the main types of values and associated valuation methods used in the hydroelectric industry, as well as opportunities to integrate the impacts of climate change. Finally, **Section 1.3** lists the climate-sensitive subcomponents related to the calculation of asset revenues, costs and useful life. It concludes by highlighting the second objective and main focus of the rest of the Guidebook: provide the methods to integrate climate change data into energy production for value modeling through the income-based method (highlighted by the yellow path on **Figure 2**).

1.1. Context of valuation

Accurate, current information about asset value supports two main types of business activities: decision-making and reporting (**Figure 2**, Columns 1 and 2). Knowledge of an asset's value can inform decisions about new project development, whether to acquire, sell or improve existing assets, as well as about energy contracts and power agreements. Asset valuation also supports the disclosure of accurate financial and economic information to external entities, such as: regulatory bodies that enforce environmental and social regulations; authorities that issue licenses and permits; parties to sale or purchase agreements; lenders and insurers (Benedetti et al., 2018; Blanchet et al., 2018; C. Kornelsen et al., 2019; Caron-Périgny et al., 2019; Sagan et al., 2019). In addition, asset values are often included in tax returns and shareholder reports. Financial information can, in turn, inform decisions about business activities. Asset valuation can also improve assessments of risk and resilience.

How frequently an organization evaluates assets varies according to context. An organization considering an investment might want to know the value of a particular asset at a specific point in time, for instance. The need for asset valuation can also be cyclical, such as to support financial and tax reporting, or to meet licensing or financing requirements. The available time to produce a valuation also varies by context: from several months or years when developing a new project; to a few weeks for the due-diligence processes needed to acquire an asset. Organizations may also be interested in the valuation of assets for the time periods presented in **Table 2**.

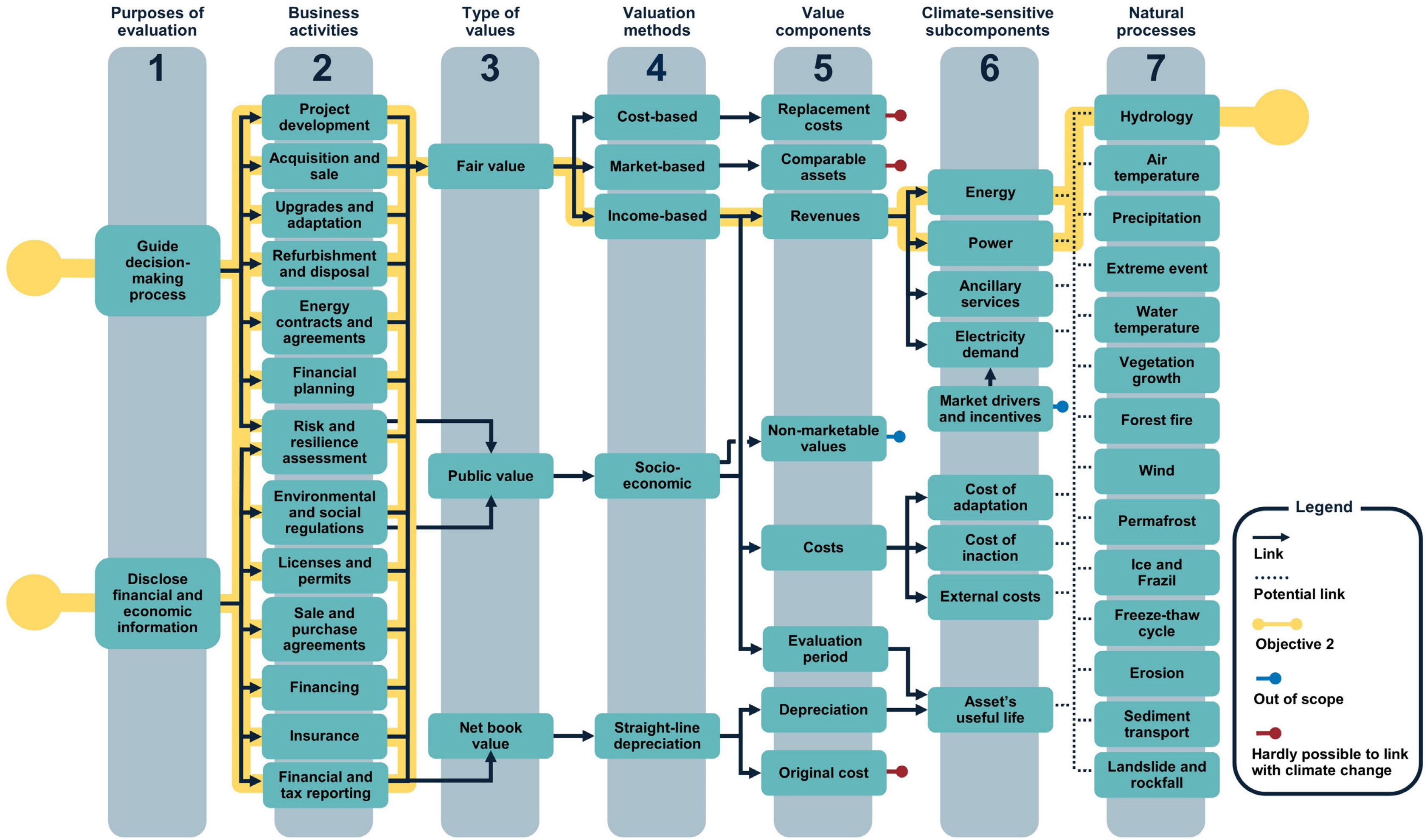


Figure 2 Framework for the integration of climate change into the valuation of hydropower assets

Table 2 Evaluation periods for hydroelectric business activities (Benedetti et al., 2018; Blanchet et al., 2018; C. Kornelsen et al., 2019; Caron-Périgny et al., 2019; Sagan et al., 2019)

Period (years)	Business activities
5-15	Financing; acquisition and sale; energy contracts and power agreements
20-30	Financial planning; acquisition and sale; project development; upgrades and adaptation; energy contracts and power agreements
50-100	Licenses and permits; environmental and social regulation; development projects; upgrades and adaptation; risk and resilience assessment; refurbishment and disposal

1.2. Types of value and opportunities for including climate change

Based on time constraints and nature of business activity, three types of value may be calculated: fair value, public value and net book value. Section 1.2 presents these types of value and associated valuation methods used in the industry, as well as opportunities to include climate change impacts.

1.2.1. Fair value

Fair value is the price that would be obtained by selling an asset in an orderly transaction between market participants at the measurement date. International Financial Reporting Standards (IFRS) set out three valuation methods to assess fair value: cost-based, market-based and income-based. In practice, note that multiple methods may be used to develop an appropriate level of confidence in a final valuation.

1.2.1.1. Cost-based method

The cost-based method offers little possibility of incorporating climate change impacts. This method aims to quantify replacement cost: the amount of money required to replace or replicate the service capacity of an asset. It ignores any revenue stream generated by the asset and focuses instead mostly on construction costs. Eventually, construction costs could integrate climate change as engineering practices, socio-environmental factors and input prices adapt to climate change. Figure 2 uses a red symbol in Column 5 to highlight the difficulty of incorporating climate change impacts into assessment of replacement costs.

1.2.1.2. Market-based method

The market-based method offers little possibility of incorporating climate change impacts. This method uses prices and other information related to transactions involving identical or comparable assets. Figure 2 uses a red symbol in Column 5 to highlight that the value of assets currently traded on the market may not yet incorporate climate change impacts, especially if these impacts can be expected to decrease the organization's overall value.

Another limitation of this method is that hydropower facilities are not frequently put on the market, making it exceedingly difficult to calculate accurate valuations. Until integrating climate change in asset market valuation becomes common practice, market-based methods will not be useful to factor for climate change.

1.2.1.3. Income-based method

The income-based method provides opportunities to value climate change impacts on projected revenues, costs and asset's useful life, unlike the two previous methods. This method considers the revenues generated and costs incurred during an asset's useful life to calculate a single, current, discounted amount known as the net present value (NPV). Organizations factor NPV into various decision-making and disclosure metrics, such as internal rate of return, revenue requirement or debt-to-service-coverage ratio. **Section 1.3** focuses on linking climate change impacts to revenues, costs and asset's useful life.

1.2.2. Public value

For the purpose of the Guidebook, public value is defined as the net benefits an asset provides to individuals, communities and companies. This differs from fair value, which considers only social and environmental costs and benefits in particular contexts: when business income is affected; when imposed by regulators; or when integrated into a social responsibility framework. Some of these costs and benefits are difficult to quantify, especially when they are not marketable commodities or when they affect people not directly involved with the asset. Socio-economic evaluation methods are helpful for considering non-marketable aspects such as public safety, the social benefits of energy reliability, and environmental, historical and cultural impacts. For example, an assessment of risk and resilience may consider the impact that a potential flood could have on public safety. Regulatory bodies may require a socio-economic valuation of environmental impacts for license renewal, or a socio-economic valuation of a population relocation associated with a proposed development project. Climate change impacts could be incorporated into the evaluation of such non-marketable aspects and be considered by regulatory bodies, but this is beyond the scope of the Guidebook (blue symbol, Column 5, **Figure 2**). **Section 1.3** explores climate-sensitive subcomponents of marketable revenues, costs and asset's useful life.

1.2.3. Net book value

By considering the influence of climate change on a hydropower asset's useful life, net book value could integrate climate change impacts. Net book value is the amount an organization records as the asset's value for accounting purposes, mainly for tax and financial reporting. It is calculated as an asset's original cost minus accumulated depreciation, depletion, impairment and amortization. Depreciation is calculated using the straight-line depreciation method over the useful life of the asset. Since generating facilities, dams and reservoirs have long lifespans – 40 to 125 years – climate change has the potential to influence their capacity over the long term. This is addressed in **Section 1.3**. The original cost includes expenditures directly attributable to acquisition, such as the costs of materials, contracted services, direct labour, interest and borrowing. Column 5 of **Figure 2** uses a red symbol because these past expenditures – original cost – will not have fully incorporated climate change impacts, especially for older assets.

1.3. Impacts of climate change

The impacts of climate change on each natural process differ regionally, which makes it impossible to generalize their influence on the value of hydropower assets. For example, temperatures are expected to increase faster in northern latitudes than in equatorial latitudes. Another example is that some regions will experience increased precipitation, while others will experience decreased precipitation. While climate change is often considered from a global perspective, such as a global increase in average temperature of 4.9°C (Moss et al., 2010) by the end of the century (according to the worst-case emissions scenario), each natural process must be evaluated regionally to fully understand the impacts of climate change on asset values. **Table 3** can help with such evaluations; it illustrates the potential links between climate-sensitive subcomponents (Column 6 of **Figure 2**), natural processes (Column 7 of **Figure 2**) and climate change.

1.3.1. Impacts of climate change on revenues

According to the type of asset – run-of-river or reservoir – and the scale of the valuation task – individual asset, hydropower fleet or portfolio – estimation of future revenues involves projections of future provision of energy, power and ancillary services. For example, the storage capacity of a reservoir may enable the creation of additional value through power generation and ancillary grid services. Accurate quantification of a hydropower asset's potential revenues must account for the full range of hydropower products, balanced with expected future electricity demand. Projections of electricity demand are particularly important when estimating the future revenues of plants with the operational flexibility to produce electricity when demand is high (peak). As shown in **Table 3**, impacts of climate change on hydrology and air temperature can be assessed to investigate impacts on regional supply and demand, and thus, on future revenues.

Issues related to climate change across the economy also inspire changes in market drivers and incentives, affecting the future demand for hydroelectricity. For instance, changes in public policy, consumption patterns and market trends for renewable energy will all affect future revenues. Since general concerns rather than specific natural process drive these changes, Column 6 of **Figure 2** uses a blue symbol to indicate that market drivers and incentives are beyond the scope of this Guidebook.

1.3.2. Impacts of climate change on costs

Costs sensitive to climate change are divided into three subcomponents (adaptation, inaction and external). Cost of adaptation is defined as the cost for an organization to manage a risk or to take advantage of an opportunity associated with climate change's modification of one or more natural processes (listed in Column 7 of **Figure 2**). Cost of inaction refers to the additional expenses incurred to reduce damages or losses due to the failure to adapt to, or take advantage of, such modifications. While adaptation strategies incur implementation costs, a growing body of evidence indicates that inaction is more expensive (Canadian Electricity Association, 2016). **Appendix C** of the Hydropower Sector Climate Resilience Guide (IHA, 2019) documents a range of potential climate change impacts on project components that can help to evaluate future costs.

External costs are those imposed by a third party and that are beyond the control of the asset owner. They are independent of an organization's efforts to adapt, and include costs related to socio-environmental constraints, insurance, water licenses, interest rates, etc. **Table 3** details the potential impacts of climate change on external costs.

1.3.3. Impacts of climate change on an asset's useful life

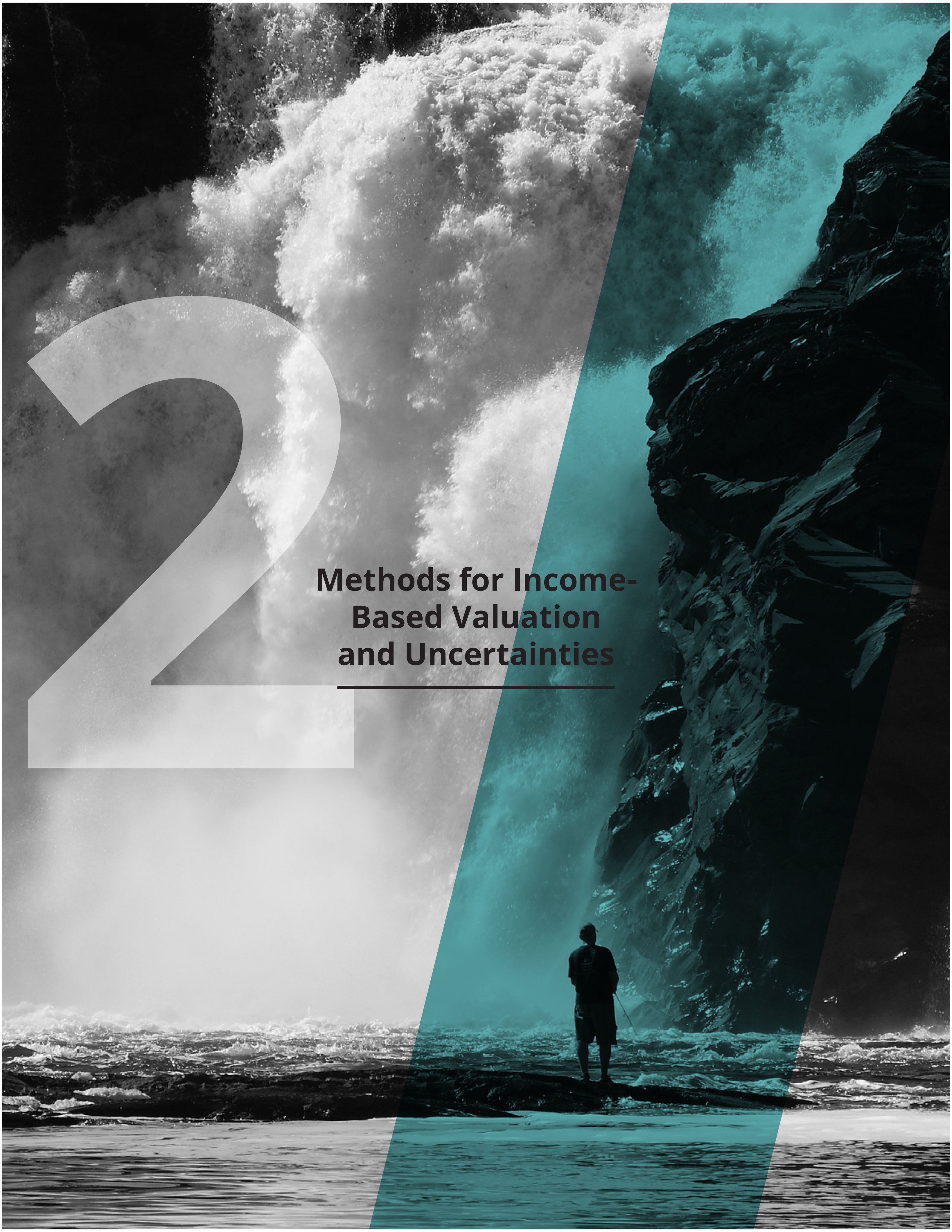
Hydropower plants are frequently cited as a type of infrastructure particularly vulnerable to climate change impacts (Boyle et al., 2013; Canadian Electricity Association, 2016). Extreme short-term events such as large storms, along with incremental climate change, can affect an asset's functional life by exceeding the design criteria used for its construction, therefore damaging the structure, or by altering maintenance practices. Foundation materials, for instance, may turn to be inadequate for future conditions. **Table 3** links natural processes and the potential impacts of climate change on an asset's useful life.

Table 3 Main impacts of climate change on the value subcomponents of hydropower assets

Climate-Sensitive Subcomponents	Natural Process	Climate Change Impacts	Reference
Revenues			
Energy	Hydrology	Changes in inflow volumes, and seasonal/monthly/daily patterns can influence the amount and timing of energy production.	(Arsenault et al., 2013; Haguma et al., 2017; Kao et al., 2015; Madani and Lund, 2010; Marie Minville et al., 2009)
Power	Hydrology	Change in inflow volumes and seasonal/monthly patterns can influence the availability of water for power generation.	(Caron-Périgny et al., 2019)
Ancillary services	Hydrology	Change in inflow volumes and seasonal/monthly patterns can influence the availability of water for grid support.	(Benedetti et al., 2018; Forrest et al., 2018)
Electricity demand	Air temperature	Increasing air temperatures modify energy demand for cooling in summer and heating in winter, and modify daily demand profile.	(Isaac and Van Vuuren, 2009; Jaglom et al., 2014; Lafrance et al., 2016; Manitoba Hydro, 2015; Mideksa and Kallbekken, 2010)
Costs			
Costs of adaptation	All	Impacts of climate change on project components requiring structural and functional adaptation measures. Each adaptation measure can represent a future cost.	Appendix C of the Hydropower Sector Climate Resilience Guide (C. Kornelsen et al., 2019; Caron-Périgny et al., 2019)
Costs of inaction	All	Inaction – failing to implement adaptation measures – can lead to future costs due to climate change impacts on project components.	Appendix C of the Hydropower Sector Climate Resilience Guide (IHA, 2019)
External costs	Hydrology	Change in hydrology can influence socio-environmental constraints on regulated flow and increase or decrease production costs.	(Caron-Périgny et al., 2019)
External costs	Hydrology	In regions where the risk of flood increases, potential loss of active storage due to flood-control measures could decrease energy production and power potential.	(IHA, 2019)
External costs	Hydrology	Change in inflow volumes and water availability can increase/decrease costs of water licenses.	(Benedetti et al., 2018; Blanchet et al., 2018)
External costs	Hydrology	Change in inflow volume and water availability can influence lenders' perception of risks and increase interest rates.	(Benedetti et al., 2018; Blanchet et al., 2018)
External costs	Extreme events	Change in extreme events intensity and frequency can increase insurance premiums.	(Benedetti et al., 2018; Blanchet et al., 2018; Caron-Périgny et al., 2019)
Evaluation period and depreciation			
Asset's useful life	Hydrology	Change in the hydrologic cycle can change dam-design criteria.	(Groulx et al., 2019; Sagan et al., 2019)
Asset's useful life	Freeze-thaw cycle	Change in freeze-thaw cycle can influence the durability of an asset's foundation materials and components.	(Groulx et al., 2019)
Asset's useful life	Extreme events	Change in intensity and frequency of extreme events can increase risk of breach and threaten asset integrity.	(Caron-Périgny et al., 2019; Sagan et al., 2019)

1.3.4. Need for an effective method

The rest of the Guidebook focus on its second objective: provide the methods to integrate climate change data into energy production for value modeling through the income-based method, as per the yellow path in **Figure 2**. A method is still needed to integrate climate change impacts into the other climate-sensitive subcomponents identified: provision of power and ancillary services, electricity demand, cost of action, cost of inaction, external costs and the useful life of assets. The amount of scientific knowledge about the impacts of natural process varies by subcomponent, however. Considerable research exists about the influence of air temperature on electricity demand (Isaac and Van Vuuren, 2009; Jaglom et al., 2014; Lafrance et al., 2016; Manitoba Hydro, 2015; Mideksa and Kallbekken, 2010), for instance, while relatively little research has been done into the impacts of climate change on landslides and their associated costs (Cloutier et al., 2016). Foremost is the need to clarify which natural processes are likely to trigger changes in asset value. This knowledge will support the development of reliable methods for the integration of climate data.



2

Methods for Income-Based Valuation and Uncertainties

The following section presents an overview of the approach to evaluate an asset using the income-based method and focuses specifically on climate and hydrology. Section 2.1 looks at the traditional method of asset valuation; Section 2.2 explains the method to integrate climate change using the income-based approach; and Section 2.3 considers the associated uncertainties.

2.1. Traditional valuation method

The traditional method relies on a hydrologic baseline consisting of streamflow observations on site, transposed from another site or of a reconstruction by water balance (inflow). It is traditionally considered as the best representation of the future. As shown in Figure 3, the hydrologic baseline starts the modeling chain and feeds an energy model to produce an energy projection. The projection is a time series at the daily, monthly or seasonal time step (for more information on energy models, refer to Stoll et al., (2017)). The energy model takes into account asset characteristics, operational management rules and constraints, as well as energy demand, to calculate the energy projection. Statistics such the long-term average are computed from the daily energy projection and are inputs to produce a value projection with the value model. The value model can also take as input the median, low and high percentiles of annual and monthly production.

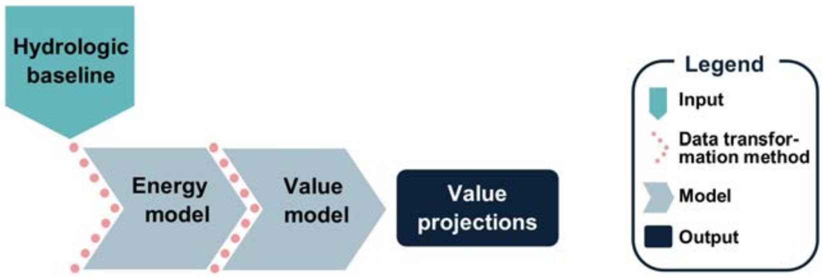


Figure 3 Typical modelling chain for the traditional valuation method

Figure 4 illustrates the traditional valuation practice. In this example, the hydrologic baseline consists of 30 years of past streamflow data (from 1986 to 2015). The hydrologic baseline is copied three times to produce a 90-year scenario from 2016 to 2105. Energy and revenues based on this scenario are computed for the future period (2016 to 2105) with simplistic model assumptions for illustration purpose only.

Note that some business activities will not necessarily rely on the complete modeling chain described previously. For example, when organizations negotiate energy contracts and agreements, they may be interested only in annual energy. Therefore, they will use the hydrologic baseline to feed the energy model and produce an energy projection to compute annual energy, without using a value model at the end of the modeling chain.

THE TRADITIONAL METHOD AND CLIMATE CHANGE

As climate change is already underway and already has had an impact on the hydrologic baseline, the traditional method cannot be deemed a valuation method without climate change: by design, it intrinsically considers the changes that have already occurred. However, the method needs to be updated to take into account future changes that differ from recent ones, as the hydrologic baseline may no longer be the best representation of the future.

A)

B)

C)

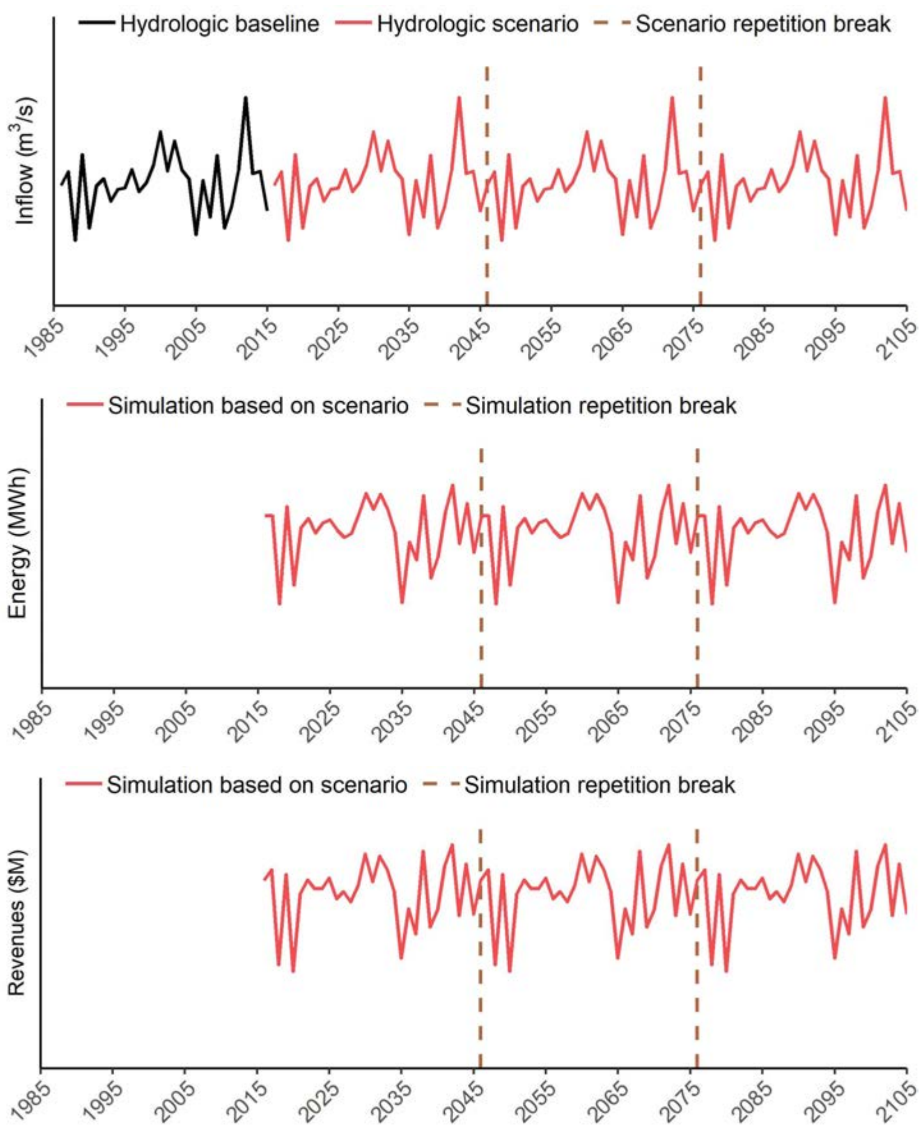


Figure 4 Example of the traditional valuation method; panel A) shows inflows, B) energy and C) revenues.

2.2. Valuation method with climate change

To include climate change in asset valuation, one needs to revisit the hypothesis that the hydrologic baseline (past hydrology) provides the best representation of the future. Solely considering the hydrologic baseline may no longer be the best option. The hydrologic baseline should be considered in conjunction with hydrologic simulations informed by greenhouse gas and aerosol emissions scenarios, as well as climatic simulations. **Figure 5** describes the modeling chain fed with emissions scenarios leading to a valuation incorporating climate change.

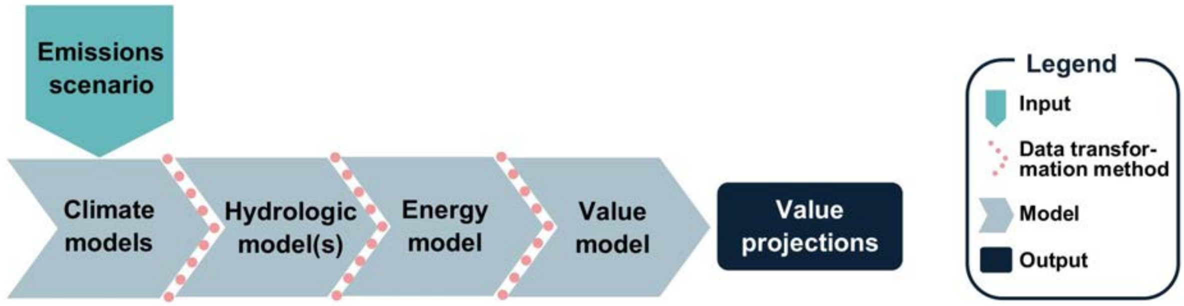


Figure 5 Typical modeling chain for valuation with climate change

One of the main challenges of the valuation with climate change is that the practitioner must combine two sets of simulations: one based on the baseline (black line in **Figure 6**); and one based on climate change (gray lines in **Figure 6**). Both sets feature interesting and useful information; the next sections of this Guidebook provide guidance on how to use this information.

As other documents better explain many of the concepts presented in this section, the Guidebook provides short summaries along with references to supplementary materials. The *Guidebook On Climate Scenarios – Using climate information to guide adaptation research and decisions* by Charron (2016), is recommended as an entry point for understanding scientifically sound climatic scenarios (the beginning of the modeling chain).

Emissions scenarios: As shown on **Figure 5**, the method with climate change starts with greenhouse gas and aerosol emissions scenarios. Numerous scenarios exist to represent the range of future emissions based on variables such as population growth, economic growth, government policies, etc. The Integrated Assessment Modelling Consortium (IAMC) develops these emissions scenarios at the behest of the Intergovernmental Panel on Climate Change (IPCC) and updates them every few years to reflect socio-economic and scientific developments. When this Guidebook was published, Representative Concentration Pathways (RCPs – Moss et al., 2010) were the most recent scenarios. The next family of scenarios is called Shared Socioeconomic

Pathways (SSP) (Sanderson et al., 2018; O'Neill et al., 2014; Hausfather, 2018).

- **Climate models:** Several climate-modeling centers around the world join forces in the Coupled Model Intercomparison Project (CMIP) and use the IPCC's emissions scenarios in climate models to produce climatic projections of the future climate in addition to simulations of the recent past, going back to 1850. The climatic projections of CMIP5, the fifth and previous CMIP experiment, come from more than 20 different models and are available for the years 2005 through 2100 (Taylor et al., 2012). They typically include many variables, such as daily temperature, precipitation, runoff, relative humidity, wind and many others. New climatic simulations are made available periodically to take into account new emissions scenarios and climate models upgrades. The CMIP6 climate projections, which start in 2015 until 2100, are now complete and available, although, at the time of publication of this Guidebook, there are still many analyzes to be done.
- **Data transformation method:** Models (climate models, as well as the other models in the modeling chain) are by nature a simplification and therefore produce imperfect simulations (see the Box Need for Data Transformation Methods at the end of this subsection). Therefore transformation methods may be required on model data at various points during the modeling chain, as the pink dotted chevron in **Figure 5** illustrates. **Section 3** presents the most common data transformation methods. Downscaling techniques may also be required, specifically for climatic simulations. This Guidebook does not address these techniques, as they are extensively covered in many other documents (e.g. Maraun and Widmann, 2018).
- **Climatic simulations:** At this point in the modeling chain, the practitioner has two options for climatic simulations, each with advantages in particular circumstances. Option one: use climatic simulations based on climate models and the appropriate data transformation method. Option two: use a weather generator that considers trends in climate models to produce climatic simulations. A weather generator is a numerical model that produces synthetic climatic simulations based on the statistical characteristics of observed weather.
- **Hydrologic model:** The climatic simulations are used to drive a hydrologic model to produce hydrologic simulations. The hydrologic model, after proper calibration and validation with observations (see **appendices F** and **G**), is typically driven with temperature and precipitation data taken from the climatic simulations, although more complex models might require other climate variables. Different types of hydrologic modeling exist for different purposes; in the valuation process, continuous hydrologic modeling is needed (Beven, 2011; Hingray et al., 2015), rather than design flood modeling, which is mainly used for infrastructure design.

- **Energy and value model:** The hydrologic simulations are then fed into the energy model to create energy simulations. The same statistics as in the traditional method are used to drive the valuation model.

Figure 6 shows an example of the implementation of the modeling chain with climate change, where the hydrologic baseline is transformed into energy and eventually revenues. They are referred to as simulations based on the baseline – simulations made with a model or a series of models and fed by the baseline. These simulations are available only for the years of the baseline. **Figure 6** also shows hydrologic, energy and revenue simulations based on emissions scenarios and climatic simulations. These are referred to as simulations integrating climate change. These simulations are available for both the past and the future, as they rely on climate models/weather generators rather than solely on the baseline.

Figure 6 also illustrates a main challenge of the valuation with climate change. In this example, the hydrologic, energy and revenue simulations integrating climate change have a negative bias. The bias is more obvious in the energy and revenue simulations, where the simulation based on the baseline (in blue) is located above the ensemble of simulations integrating climate change (in gray). In this example, the bias originates from the hydrologic model, spreads through the rest of the modeling chain and is problematic for a comparison between the traditional valuation method and the valuation method with climate change. It can also trigger a loss of confidence in the valuation method with climate change.

Finally, one of the main differences between the traditional valuation method and the valuation method with climate change is the number of climatic/hydrologic time series that must be used. When working with the traditional method, there is usually a limited set of climatic/hydrologic time series to work with (see **Figure 4** of **Section 2.1**). Exceptions occur when organizations work with stochastic and resampling approaches. When working with climate change, the ensemble approach is typically used to account for uncertainties related to unknown future events and processes (see **Section 2.3** – Source of uncertainty). The ensemble approach consists of using several options and combinations at each step of the modeling chain (emissions scenarios, climate models, post-processing techniques, etc). Climate change studies can therefore easily become data-intensive projects; the practitioner will have to deal with several emissions scenarios, possibly tens of Global Climate Model (GCM) results for tens of watersheds (e.g. Guay, Minville and Braun, 2015). **Figure 6** presents only three simulations, although generally many others are available. Uncertainties in the energy simulations and the revenue simulations can also be considered and integrated in the ensemble approach. The next section discusses the importance of the ensemble approach and the uncertainties of the value modeling chain.

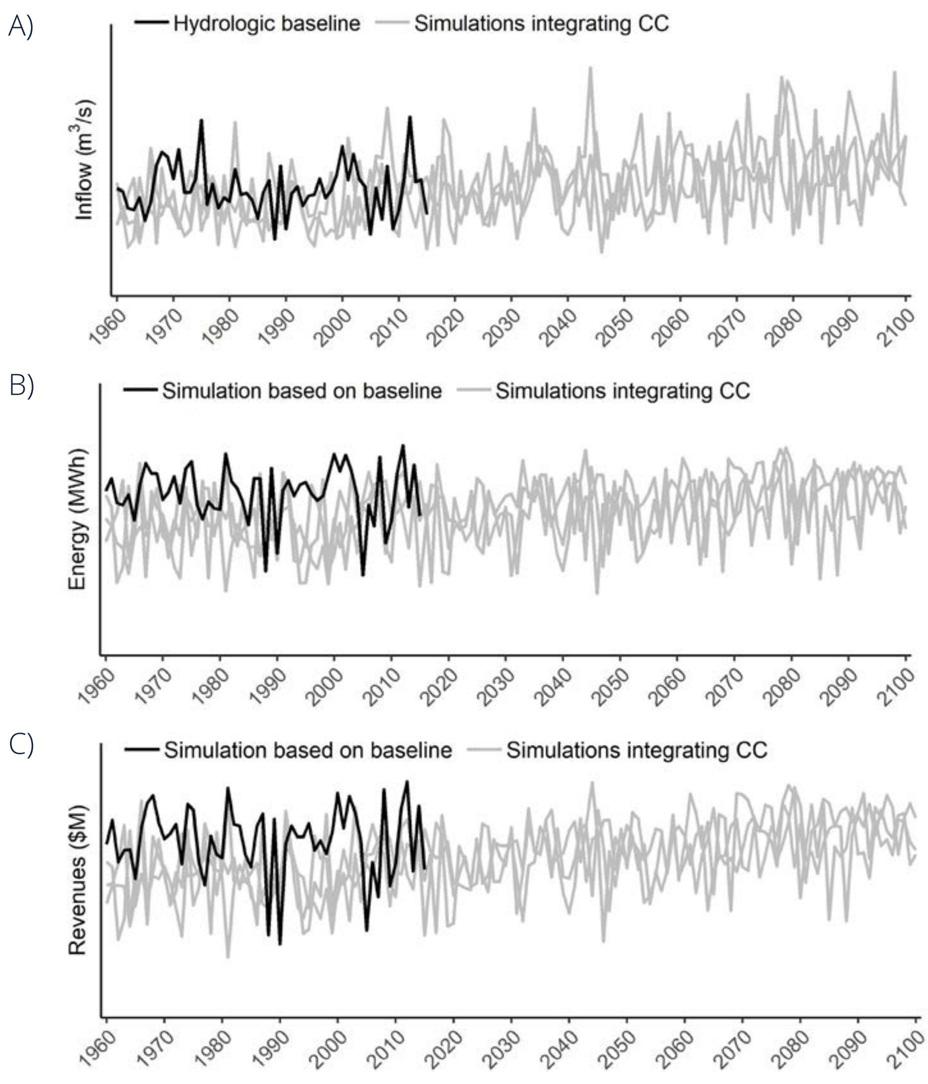


Figure 6 Example of the valuation with climate change along with past inflows, energy and revenue. Panel A) shows inflows, B) energy and C) revenues.

NEED FOR DATA TRANSFORMATION METHODS

In an ideal world, the outputs of the climate, hydrologic, energy and valuation models would create an accurate simulation of real-world physics. In reality, however, a model is an abstraction of reality – a plausible reality. Real-world physics are simplified into several numerical equations. Therefore, the model is a simplification of the system, and produces imperfect and biased simulations.

Figure 7 helps explain model bias and the need for data transformation methods. The hydrologic baseline is presented, along with hydrologic simulations fed with raw climatic simulations (direct output from the climate models) and bias-corrected climatic simulations (output from climate models with a data transformation applied) over concomitant years. The hydrologic simulations fed with raw climatic simulations show major biases (overestimation of flows in this case) that lead to problems later in the modeling chain, while bias-corrected simulations show good agreement with the hydrologic baseline.

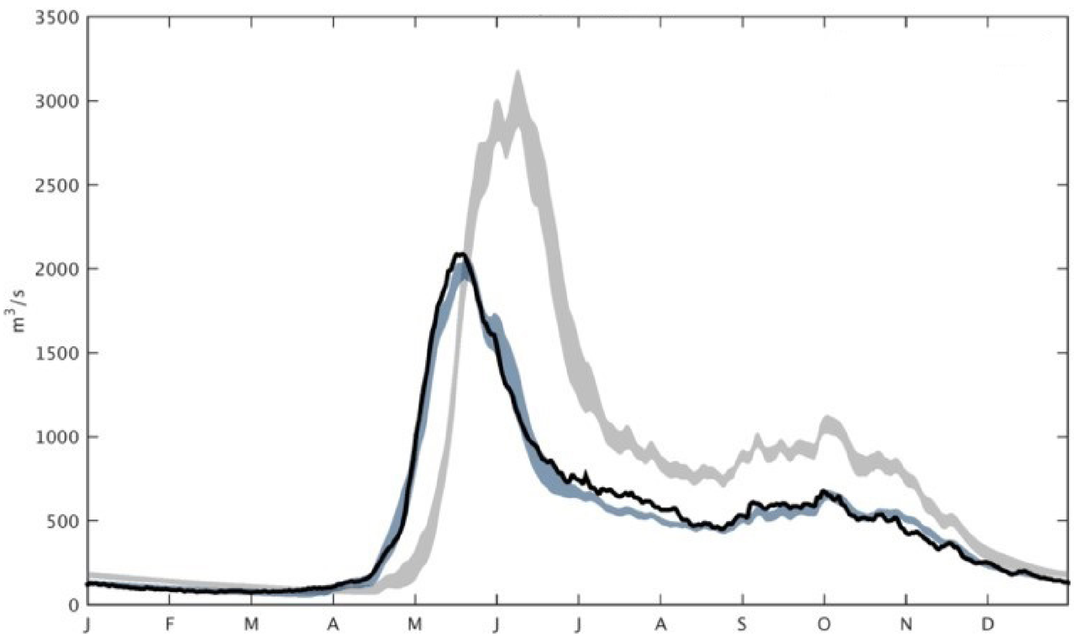


Figure 7 Annual hydrograph of hydrologic baseline and simulations. The figure presents flow over time of hydrologic baseline (black), hydrologic simulations produced with raw climatic simulations (gray) and hydrologic simulations fed with bias-corrected climatic simulations (blue) over concomitant years. This example demonstrates that the shape of the black line is well represented by the shape of the gray line, but that the gray line is biased high. Once the bias is removed, the model projection (blue) is fairly reprensative of observations.

2.3. Sources of Uncertainty

There is scientific consensus that the global climate is changing and will continue to change in the future. Despite the certainty of climate change, uncertainties exist about the magnitude of future greenhouse gas and aerosol emissions, the climate system's response to these emissions and how climate changes translate to hydrologic changes. These uncertainties compound with each step of the modeling chain in what Jones (2000) termed the "cascade of uncertainty." The result can be a significant amount of inherent uncertainty. This uncertainty exists whether or not it is characterized and considered by the practitioner.

Although decisions are easier to make if the decision-making process ignores some uncertainty, this does not guarantee good decisions. For instance, by considering only one emissions scenario or only a few GCMs, the practitioner can miss what will actually happen in the future and the associated consequences. The practitioner is less likely to miss what will actually happen in the future by exploring all possible combination of emissions scenarios, models and methods.

The ensemble approach (combination of emissions scenarios, models and methods) is used to evaluate the cascade of uncertainty. However, this approach can become challenging because the number of combinations rises quickly and their integration in the modeling chain can become unrealistic because of constraints such as computational time.

Understanding the uncertainty inherent in each step of the modeling chain is the first step in the ensemble approach: more resources can be allocated to characterize the biggest sources of uncertainty. **Section 2.3.1** defines the sources of uncertainty in the modeling chain, while **Section 2.3.2** considers the relative magnitude of various sources of uncertainty. The uncertainty related to some of the methods presented in **Section 3** is also presented here for the sake of clarity. Other strategies to work with the ensemble approach are provided in **Appendix I** – Best and good practices for the ensemble approach and **Appendix C** – GCM selection methods.

2.3.1. What are the sources of uncertainty?

Table 4 presents the sources of uncertainty in the modeling chain, as well as approaches to quantifying them (see **Section 2.3.2** for relative magnitudes).

Table 4 Sources of uncertainty at each step of the modeling chain

Item	What are the sources of uncertainty?	How is uncertainty quantified?
Emissions scenarios	▪ Greenhouse gas emissions scenarios reflect our current understanding and knowledge of population, economic growth, conflict, technology and international policies (IPCC, 2013). These factors are significant sources of uncertainty; for example, mitigation policies can play an important role in regulating anthropogenic emissions (Charron, 2016) and it is challenging to project the emergence of technology that does not yet exist.	▪ The IPCC has defined several emissions scenarios spanning a range, to reflect alternative visions of how the future may unfold (IPCC, 2013). ▪ The uncertainty from emissions scenarios is typically quantified by the range of results obtained across all scenarios.
Climate Projections: Climate Models	▪ GCMs divide the earth into 3D cells and use equations to approximate reality (IPCC, 2013). Increasingly more processes are added as scientific understanding advances, but still many approximations and assumptions are necessary because the earth is too complex and chaotic to fully represent all aspects scientifically (Wilby, 2010). This creates a significant source of uncertainty. ▪ In addition, climate models have to parameterize (simplify) processes that occur at small spatial and temporal scales. This creates an additional source of uncertainty; for example, GCMs do not explicitly model clouds (Sillmann et al., 2017).	▪ CMIP regroups dozens of GCMs from centers around the world. These models include various processes and parameterizations. The uncertainty from climate models is typically approximated by the range of results obtained from CMIP (IPCC, 2013).
Climate Projections: Natural Variability	▪ Even if scientists perfectly understood the earth system and computing capabilities were unlimited, there would still be uncertainty in the climate system simulations due to its chaotic behavior. This behavior creates natural variability (Deser, Knutti, et al., 2012; Ignazio Giuntoli et al., 2018). ▪ Natural variability contributes uncertainty to climate projections; for example, climate trends on decadal timescales can have opposite trends to that of overall climate changes (Charron, 2016;Deser, Phillips, et al., 2012; Evin et al., 2019).	▪ Natural variability in CMIP ensembles is represented by the diversity of initial conditions in the different models (Deser et al., 2014; Hawkins et al., 2016). ▪ Some modeling centers have run single climate models multiple times with slight perturbations in the initial conditions (e.g. by changing the start date of the simulation, see Charron, 2016). This type of large ensemble can be used to estimate the uncertainty resulting from the chaotic nature of the climate (Ignazio Giuntoli et al., 2018).
Post-processing: Methods and Observation Datasets	▪ Climate models require post-processing to remove model bias (IPCC, 2013). Climate impact analyses can also require downscaling to convert from the scale of the model grid cell to that of the impact model. These methods make assumptions about the distribution of the data and about aspects of the climate that will not change in the future (Maraun and Widmann, 2018), and some of these assumptions are questionable. ▪ Post-processing methods make use of observed data. However, there are uncertainties related to observations due to: changes in climate-station locations, observation and recording practices, site characteristics and sampling regimes; issues with interpolation; and biases toward lower-elevation, urban or coastal locations (Wilby, 2010)).	▪ Uncertainty from post-processing can be assessed by comparing different methods, or by testing the method against multiple observational datasets (Maraun and Widmann, 2018; see Appendix E – Validation of climate products). ▪ Uncertainty from observational datasets is best assessed by comparing projections that have used different datasets (e.g. Gao et al., 2019), or by comparing the datasets directly (see Appendix E – Validation of climate products).
Hydrology Projections	▪ It is in practice impossible to measure everything we would like to know about the hydrologic system (mostly due to spatial variations and limitations of measurement techniques (Pechlivanidis et al., 2011). Furthermore, it is difficult to link physical properties that can be measured at the field scale with parametric values that represent the overall behavior of the land (Wilby, 2010). Therefore, all hydrologic models remain to some extent conceptual and empirical, and rely heavily on parameters and calibration (Coron et al., 2012). This empirical nature can sometimes mean that a model that shows a good performance in the current climate might not perform well in a future climate (Lofgren et al., 2011). ▪ Uncertainties from hydrologic models can be subdivided into structural, parameter and observation uncertainties (Chen, Brissette, Poulin, et al., 2011; Motavita et al., 2019; Schaefli, 2015).	▪ Uncertainty from hydrologic models is estimated either by testing the model against observational datasets, or by comparing hydrologic projections obtained from different models (Pechlivanidis et al., 2011). The latter method enables testing for equifinality – when several model structures or parameter sets produce the same results in the calibration (flows in the case of hydrology), but may differ in their ability to project changes (Her et al., 2019; Poulin et al., 2011).

Item	What are the sources of uncertainty?	How is uncertainty quantified?
Energy Projections	▪ Hydropower operations are by nature complex to model compared to other electricity generators (Stoll et al., 2017) because of three main reasons: ◆ Lack of data regarding system characteristics ◆ Computational time constraints ◆ Limited ability to account for all applicable constraints (environmental, operational and regulatory constraints). ▪ These sources of complexity contribute in turn to uncertainty in future energy projections: applicable characteristics and constraints are difficult to account for and they may change in the future. For example, the following parameters may change: ◆ Generation system characteristics and availability (forced and planned outages of units, transformers and lines) ◆ Environmental constraints (maximum reservoir elevation, discharge limits, etc.) ◆ Regulatory constraints.	▪ Model accuracy can be tested against past generation. ▪ The impact of changing constraints and availability of components of the generation system can be simulated
Asset Valuation	▪ Along with the market's volatility and availability of information, sources of uncertainty in asset valuation stems from assumptions based on a combination of future market conditions, for example: ◆ Energy prices and tariffs ◆ Investment costs ◆ Financial life of project ◆ Inflation ◆ Taxes, subsidies and policies. ▪ Uncertainty also resides in estimation of key parameters such as discount rate and weighted average cost of capital (WACC) based on: ◆ Risk profile of the asset ◆ Capital structure ◆ Cost of capital.	▪ Uncertainty from asset valuation can be assessed with partial sensitivity analysis by testing the impact each assumption has on the overall valuation (Malovic et al., 2015). ▪ Probabilistic approaches like Monte Carlo simulations (Haguma et al., 2017) and scenario analysis (Manitoba Hydro, 2013) consider a combination of future conditions simultaneously. Valuation results are associated with statistical degree of confidence. ▪ Real option analysis assesses the option of management flexibility of an investment under evolving market uncertainty (Kim et al., 2017). It estimates the volatility of a project's value.

Note that although the conventional approach to quantifying uncertainty, using an ensemble of simulations and partitioning the variance into different components (e.g. Giuntoli et al., 2018), is an informative approach, it may underestimate the total uncertainty due to an insufficient sampling of the possible range of model and scenario results (Bosshard et al., 2013; Schaefli, 2015).

2.3.2. How do the sources of uncertainty for streamflow projections compare?

This section focuses on the importance of each source of uncertainty for streamflow projections (i.e. how much does each source of uncertainty lead to variations in streamflow projections). Note that uncertainties relating to energy and valuation models are not considered in this section. Climate and hydrologic models are presented first because they are typically the largest sources of uncertainty for streamflow projections. A short section at the end addresses other hydroclimatic variables and the time-dependence of relative uncertainty.

Climate models and hydrologic models

The greatest source of uncertainty in the modeling chain is generally considered to be the climate model (Bastola et al., 2011; De Niel et al., 2019; Feng, 2018; Kay et al., 2009; Prudhomme and Davies, 2009; Vetter et al., 2017; Wilby and Harris, 2006). However, hydrologic model uncertainty can be greater in seasons and regions dominated by processes that pose a greater challenge for hydrologic modeling, such as snow and ice processes (Bosshard et al., 2013; I Giuntoli et al., 2015; Troin et al., 2018; Vidal et al., 2016), soil moisture and groundwater processes (Her et al., 2019), and evapotranspiration processes (Hattermann et al., 2018; Sellami et al., 2016).

Emissions scenarios

Emissions scenarios are highly uncertain; for example, for CMIP5, the business-as-usual scenario (RCP 8.5) has an equivalent CO_2 concentration of more than 1,370 ppm, compared to approximately 650 ppm for the moderate scenario (RCP 4.5; Charron, 2016). The range of projections that corresponds to each emissions scenario can vary. Shen et al., (2018) showed that the hydrologic uncertainty for a high emissions scenario (RCP 8.5) was larger than that under a relatively low emissions scenario (RCP 4.5). This is because the modeling chain has a greater range of responses to the high emissions scenario. Nonetheless, a number of studies have found that, for streamflow projections, the contribution of RCPs to uncertainty is small compared to the other uncertainty sources (during the time horizons analyzed), due to the predominance of other sources of uncertainty (Arnell and Gosling, 2013; Chen, Brissette, and Leconte, 2011; Gao et al., 2019; Ignazio Giuntoli et al., 2018; Wada et al., 2013).

Natural variability

It is difficult to draw conclusions about the contribution of natural variability to uncertainty in streamflow projections because only a few relevant studies have been completed and they yield contradictory results. Chen et al., (2011) found that GCM initial conditions (used to represent natural variability) were a major contributor to uncertainty for certain hydrologic variables. In contrast, Giuntoli et al., (2018) found that natural variability was not a large contributor to uncertainty. However, natural variability is reduced in the Giuntoli et al. (2018) study because they used decadal means.

Another difficulty in comparing different studies that assess degrees of uncertainty from natural variability is that the magnitude of uncertainty depends on several factors.

- **Temporal scale.** Natural variability uncertainty tends to be larger, and the time of emergence longer, for smaller temporal scales (Hosseinzadehtalaei et al., 2017; Van Uytven and Willems, 2018; Vidal et al., 2016). Time of emergence refers to the time for the climate change signal to emerge from the noise of natural variability.
- **Spatial scale.** Variability tends to be larger at small spatial scales. For example, regional projections tend to have larger natural variability than global means, and in some cases, spatial aggregation removes variability (Evin et al., 2019; Fischer et al., 2013).
- **Geography and climate.** For example, the relative uncertainty for temperature projections is lower at the poles, due to a stronger temperature signal (Fischer et al., 2013).
- **Hydrologic variable.** The relative magnitude of uncertainty from natural variability is different depending on the hydrologic variable (Chen, Brissette, Poulin, et al., 2011; Hawkins and Sutton, 2009; Vidal et al., 2016).

Natural variability may change in the future as atmospheric dynamics change. For example, different oscillations may behave differently in the future. Some studies have inferred that inter-annual temperature variability may decrease in northern latitudes based on changes to projection ensemble spread (Carter et al., 2007; Hawkins et al., 2016). Nonetheless, most studies suggest that the total amount of natural variability will remain fairly constant in the future (e.g. Chen, Brissette and Leconte, 2011; Giuntoli et al., 2018).

Post-processing

Although climate and hydrologic models are the dominant contributors to uncertainty in the modeling chain, the uncertainty contribution from post-processing (or downscaling/bias correcting) has also been found to comprise a large fraction of the uncertainty when projecting high and extreme flows (Chen, Brissette, and Leconte, 2011; De Niel et al., 2019; Mandal and Simonovic, 2017). Gao et al., (2019) found that uncertainty of average monthly and annual streamflow due to the bias-correction data source is greater than that of emissions scenarios and less than that of GCMs for the time horizons analzed.

Time dependence

The relative magnitude of the sources of uncertainty described above varies with the projection horizon (Giuntoli et al., 2018; **Figure 8**). For instance, as the century progresses and the lead time increases, the hydrologic impacts that are driven by changes in emissions scenarios become increasingly important compared to the noise of natural variability (Ignazio Giuntoli et al., 2018). Conversely, over shorter lead times of a few decades, the climate change signal may not yet have "emerged" from the noise of natural variability (Charron, 2016). The time of emergence depends on the strength of the climate change signal (e.g. which can be stronger for certain hydrologic variables), as well as on the magnitude of natural variability (e.g. which depends on temporal scale, spatial scale, season, climate, etc.; Bosshard et al., 2013).

Plotting the uncertainty fraction attributable to different sources over time is one way to show how uncertainties change depending on the projection horizon. For example, Giuntoli et al., (2018) examined how the relative magnitude (or "partitioning") of uncertainty from the ISIMIP (Inter-Sectoral Impact Model Intercomparison Project) runoff projections for the U.S. evolves throughout the 21st Century (**Figure 8**). They found that the relative contribution of natural variability (orange) decreases over time as uncertainty of global impact models increases significantly (green). Note that these findings would be expected to differ for a different spatial scale and geography. A global hydrologic model is a type of global impact model; it uses climate change projections as inputs, and models impacts on other variables.

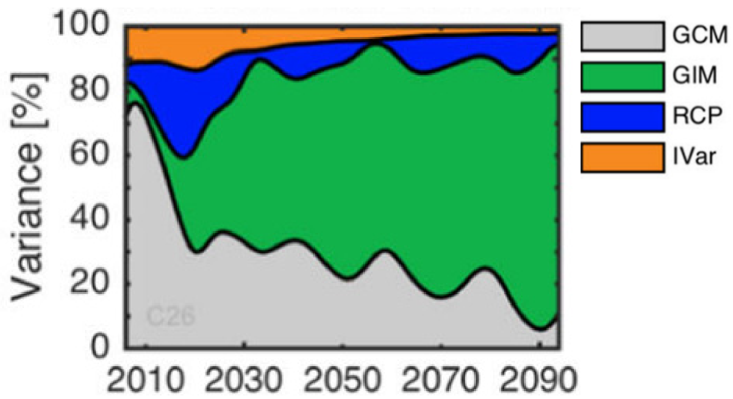


Figure 8 Fractional change in uncertainty sources for annual median runoff (calculated from daily runoff) for a selected grid cell (42.7° N–73.9° E; Albany, NY). Legend: Global Climate Model (GCM), Global Impact Model (GIM), Representative Concentration Pathway (RCP), Internal Variability (Ivar). The reference period is 1971–2005, and 10-year moving averages were used (Ignazio Giuntoli et al., 2018). Note that these findings would be expected to differ for a different spatial scale and geography.

Magnitude of uncertainty for other variables

The relative magnitude of different sources of uncertainty depends on the variables of interest. Practitioners may also be interested in projections of temperature or precipitation, including snow (e.g. for an in-house model). For these needs, the reader is directed to literature on uncertainty decomposition for temperature and precipitation (e.g. Hawkins and Sutton, 2011; Fischer, Beyerle and Knutti, 2013; Hawkins et al., 2016; Hosseinzadehtalaei, Tabari and Willems, 2017; Van Uytven and Willems, 2018; Evin et al., 2019; Gao et al., 2019).

Figure 9 illustrates the time-evolution of uncertainty sources for temperature and precipitation (similar to **Figure 8**, which shows the same for runoff). Emissions scenarios tend to be a greater source of relative uncertainty for temperature than for precipitation projections (Ignazio Giuntoli et al., 2018), whereas precipitation projections are generally dominated by GCM uncertainty and natural variability rather than emissions scenarios (e.g. Hawkins and Sutton, 2011).

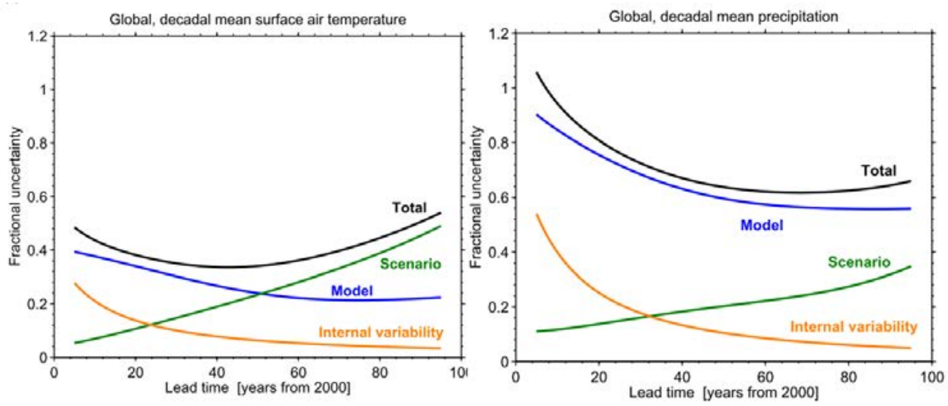
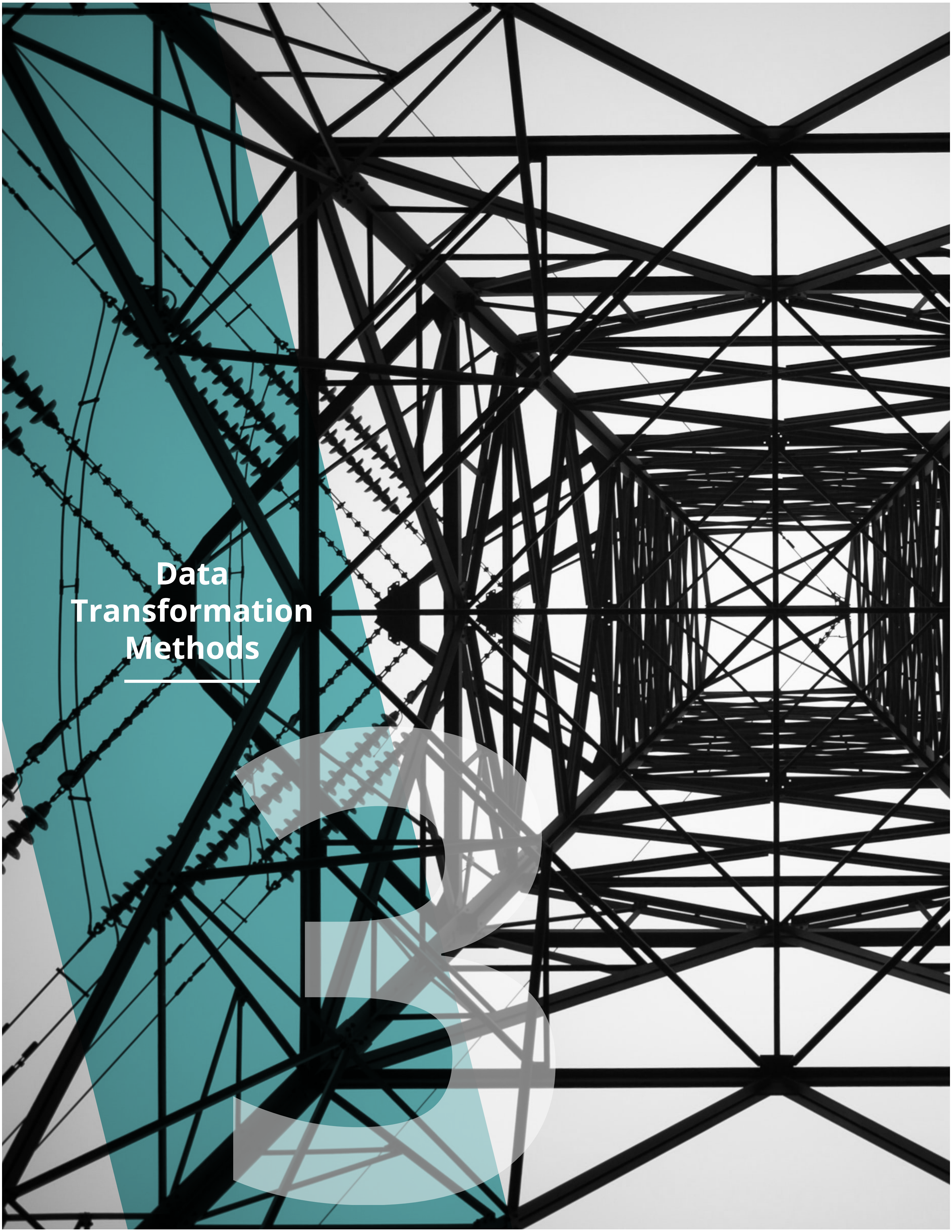


Figure 9 The fractional uncertainty in decadal global mean climate projections, defined as the uncertainty divided by the expected mean change for (left) temperature and (right) precipitation (from Hawkins and Sutton 2011)



3

Data Transformation Methods

This section presents the data transformation methods that may be needed between each step in the modeling chain outlined in Section 2. The data transformation methods can be applied to two types of time series: baseline (the data that are judged the best representation of a system's past or current state) and/or simulation (direct outcome of a model). The output of a data transformation method is a scenario.

Section 3.1 presents the direct method, which can be used on the baseline or the simulation. The reduction and the adjustment methods, presented in Section 3.2 and 3.3, respectively, are typically applied to a baseline to account for data errors, trends, biases and heterogeneities. The extension, delta method and bias correction methods, outlined in Section 3.4 through 3.6, use the baseline and simulations to produce a future scenario. Note that theoretically, these methods may be applied everywhere and several times in the modeling chain. Section 6 and 7 provide guidance on their proper use for the valuation of assets. Note that multiple definitions exist for these methods in the scientific literature. As such, each method will be defined as it is being introduced in this section.

GENERAL ASSESSMENT OF THE DATA

Prior to applying transformation methods, data should be analyzed thoroughly. This will enable the practitioner to get accustomed to the data, and to better understand biases and imperfections. Without this step, if all they look at is the result produced at the end of the modeling chain, the practitioner may miss important pieces of information. In this respect, descriptive statistics (e.g. mean, standard deviation, etc.) and classification methods are good starting points.

3.1. Direct method

The direct method, the most straightforward method, consists of applying no modifications to the data (baseline or simulation) before their integration into the next model of the modeling chain.

3.1.1. Advantages of the direct method

- Easy to implement
- No loss of information due to data transformation

3.1.2. Disadvantages of the direct method

- All characteristics in the baseline and simulation are transmitted to the next step in the modeling chain.

3.2. Reduction method

This method involves reducing the baseline time period (as shown in **Figure 10**) and can be applied when part of the time series is considered unrepresentative of the current period. This can happen when the baseline has a statistically significant trend or has statistical heterogeneities (such as an abrupt change in mean, or heteroscedasticity).

Prior to the reduction of the baseline, it is important to run relevant statistical tests. It is also relevant to identify the cause(s) of the trend – to detect and attribute (see **Appendix B** – Detection and attribution in the context of climate change) – and of the statistical heterogeneities. As explained in **Section 4**, many drivers other than climate change can lead to a data trend or heterogeneities.

3.2.1. Advantages of the reduction method

- Sample is more representative of current conditions.
- Obtain a homogeneous sample when statistical heterogeneities exist.

3.2.2. Disadvantages of the reduction method

- Loss of valuable information present in the unused part of the time series (e.g. inter-annual variability and extreme events that occurred during the unused part).
- While detection and attribution studies are recommended before implementing this method, they are lengthy and complex.

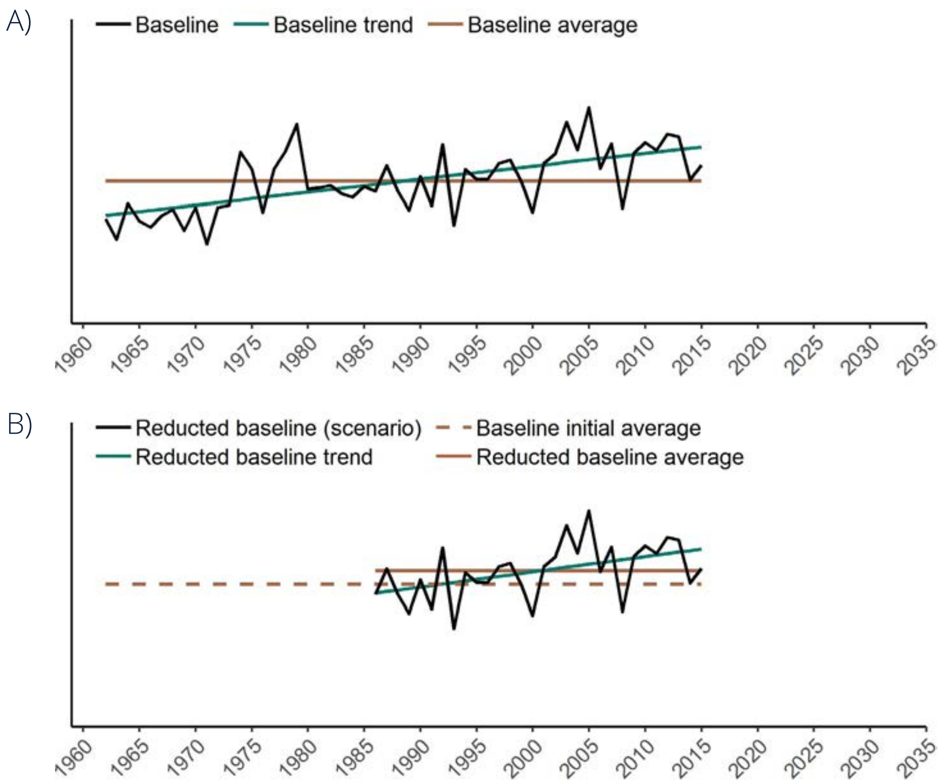


Figure 10 Example of reduction method. Panel A shows the entire baseline. Panel B shows the years considered after the reduction (the last 30 years of the baseline).

3.3. Adjustment method

This method, also known as detrending, involves adjusting the baseline to remove a statistically significant trend and make it representative of current conditions. This can be done using a correction factor proportional to time. As shown in **Figure 11**, the correction factor can be computed directly from the baseline. It can also be computed from simulations integrating climate change and other pertinent drivers (see **Section 4**), as shown in **Figure 12**. This latter option can be an interesting way to isolate the influence of a single driver, in this case climate change, within the baseline.

The correction factor proportional to time can be computed on mean values or on quantiles (see **Section 3.5** – Delta method). The correction factor can also be computed at the annual, seasonal, monthly or daily scale.

This method may be complementary to other methods. For example, bias correction or delta methods based on quantiles may benefit from being combined with an adjustment. **Section 7** discusses this topic in detail.

Note that detection and attribution prior to the adjustment is relevant (see **Section 4** and **Appendix B** – Detection and attribution in the context of climate change), as it will help the practitioner understand the physical basis of the trend.

3.3.1. Advantages of the adjustment method

- Maintains the sequence of events while removing the trend, which can be of particular interest when comparing past, present and future (Snover et al., 2003).

3.3.2. Disadvantages of the adjustment method

- Application of this method with a correction factor based on the baseline values without proper detection and attribution (see **Appendix B** – Detection and attribution in the context of climate change) can lead to adjustments that have reduced physical basis.
- While detection and attribution studies are recommended before implementing this method, they are lengthy and complex.
- Modifies the baseline mean or quantiles, and ignores the other processes, such as the modification to sequences or inter-annual variability.
- Application of this method may affect some important information about historical extreme events.
- There is a risk to overfit the data. (See **Section 7.5.3** – Over-fitting).

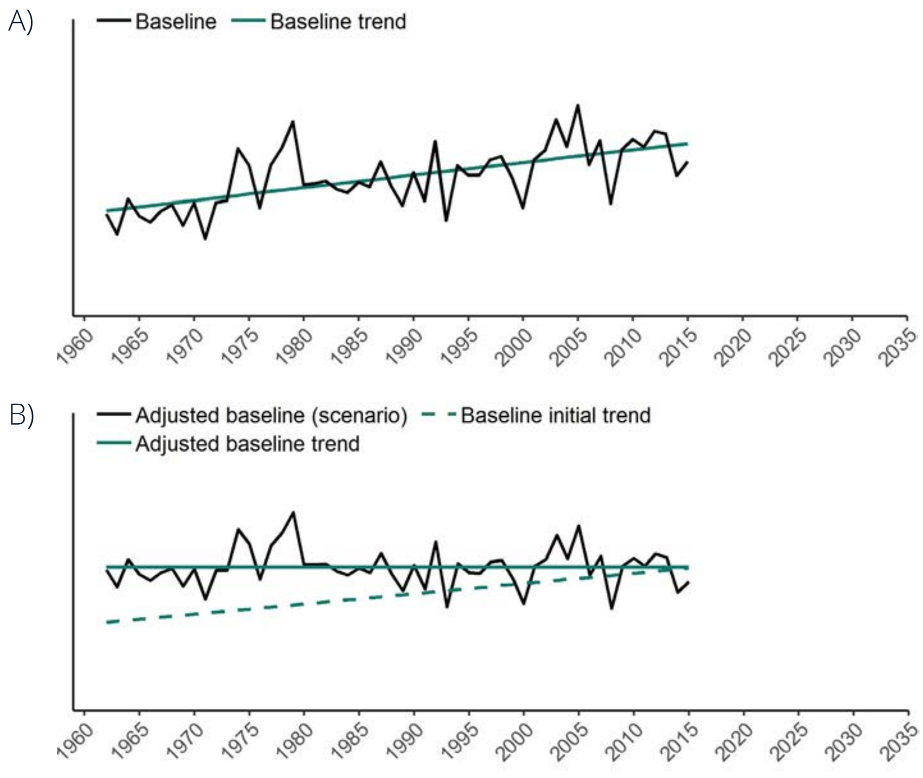


Figure 11 Example of adjustment with the correction factor computed directly from the baseline. Panel A shows the entire baseline with its trend. Panel B shows the adjusted baseline.

A)

B)

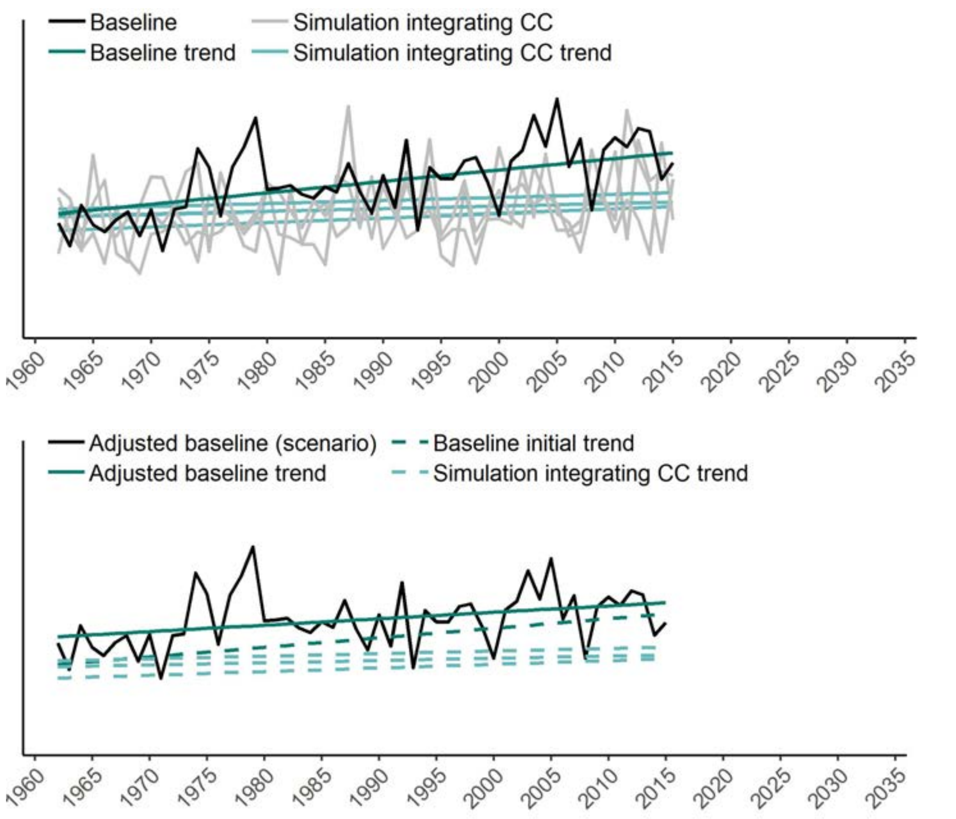


Figure 12 Example of adjustment with the correction factor computed from simulations integrating climate change. Panel A shows the baseline with its trend and the simulations integrating climate change with their respective trends. The correction factor is computed from the average of the climatic simulations trend. Panel B shows the adjusted baseline.

3.4. Extension method

This method involves an extension of the baseline, when the baseline presents a statistically significant trend, to make it representative of future conditions. It can be done using a correction factor proportional to time. The correction factor can be computed directly from the baseline (as shown in **Figure 13**) or from simulations integrating climate change and other pertinent drivers (as shown in **Figure 14**). This latter option can be an interesting way to isolate the influence of a single driver, in this case climate change, within the baseline.

The correction factor proportional to time can be computed on mean values or on quantiles (see **Section 3.5** – Delta method). The correction factor can also be computed at the annual, seasonal, monthly or daily scale.

Detection and attribution prior to the computation of the correction factor from the baseline is highly suggested (see **Section 4** and **Appendix B** – Detection and attribution in the context of climate change). If the correction factor is computed from simulations integrating climate change and other pertinent drivers, the detection and attribution is also relevant.

3.4.1. Advantages of the extension method

- Enables the comparison of past years to a similar year with climate change.
- Maintains the sequence of events, which can be of particular interest when comparing past, present and future (Snover et al., 2003).

3.4.2. Disadvantages of the extension method

- Errors in the baseline, trends, cycles and step, along with abrupt changes in and influences from past drivers, are projected into the future and transmitted to the next step in the modeling chain.
- Application of this method with a correction factor based on the baseline values without proper detection and attribution can lead to projections with reduced physical basis (see **Appendix B** – Detection and attribution in the context of climate change).
- While detection and attribution studies are recommended before implementing this method, they are lengthy and complex.
- Modifies the mean or the quantiles of the baseline. Ignores the other processes, such as the modification to sequences or even inter-annual variability.
- Ignores potential future steps and abrupt changes.

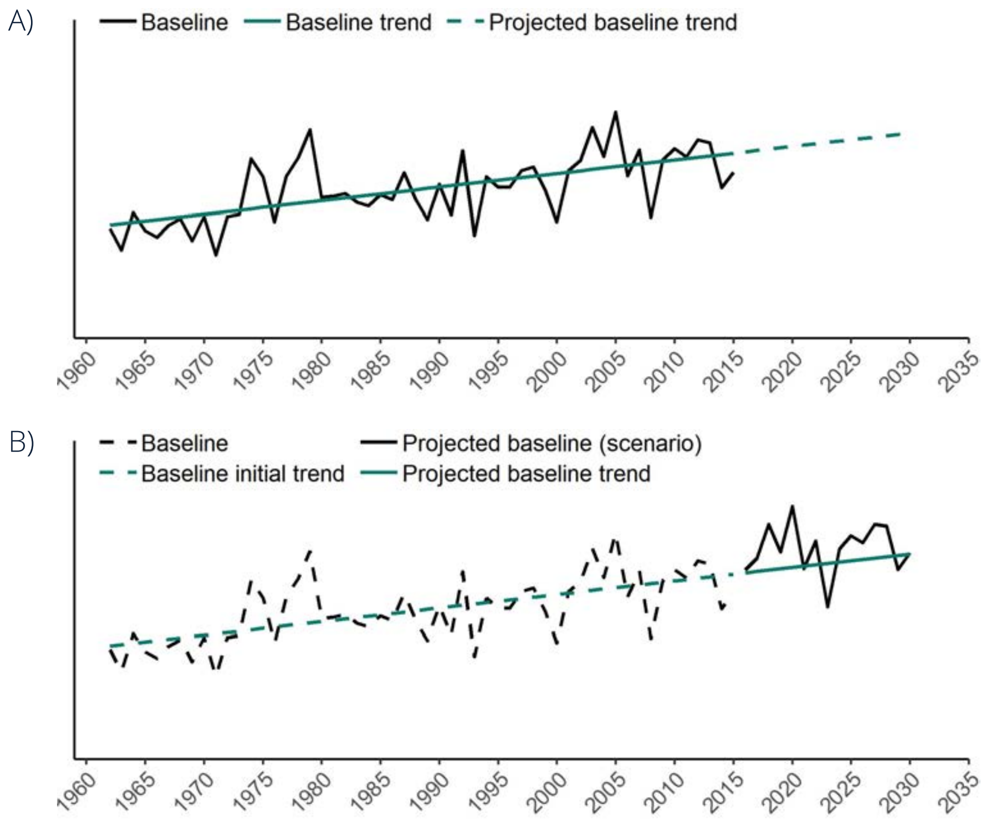


Figure 13 Example of extension with the correction factor computed directly from the baseline. Panel A shows the entire baseline with its trend and its projection in the future. Panel B shows the adjusted baseline. Note that only the last 15 years of the baseline are projected into the future.

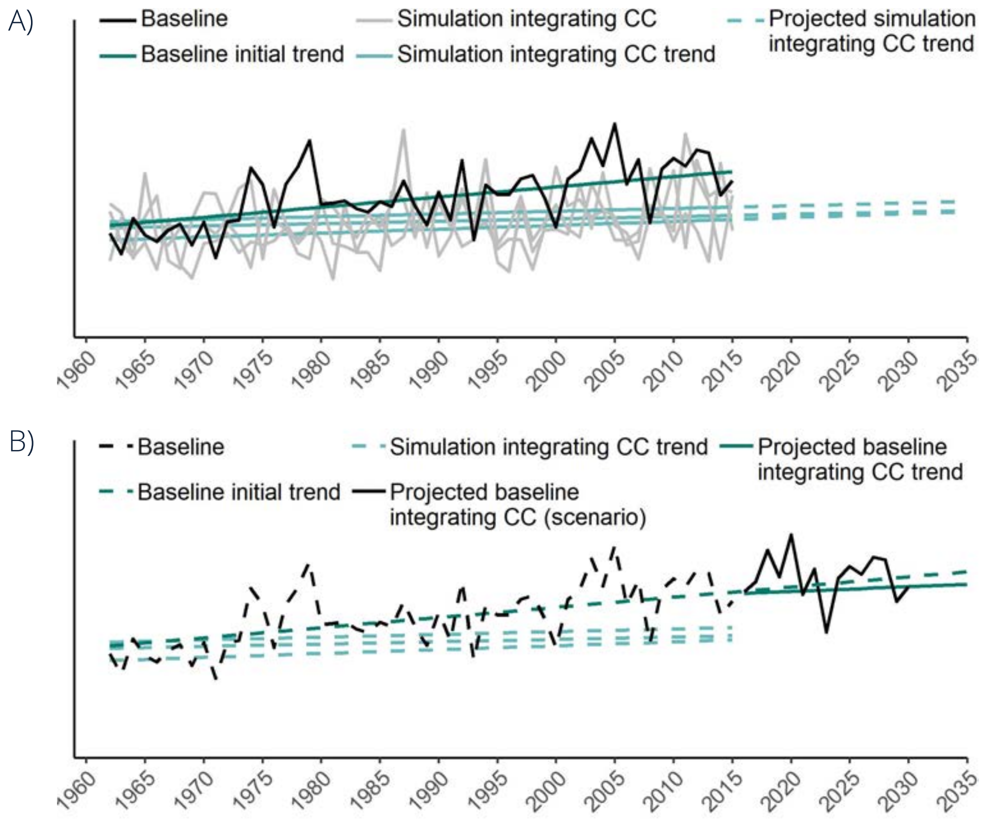


Figure 14 Example of extension with the correction factor computed from simulations integrating climate change. Panel A shows the baseline with its trend and the simulations integrating climate change with their respective trends. The correction factor is computed from the average of the climatic simulations trend. Panel B shows the baseline extended over 15 years.

3.5. Delta method

The delta method, also known as the scaling or perturbation approach, is described by Charron (2016) for climate data. The definition is generalized below to suit the needs of the modeling chain.

This method involves a perturbation of the baseline using the relative or absolute change between the simulated reference and simulated future periods within a given simulation integrating climate change. The relative or absolute change between the reference and the future is first calculated (**Figure 15A**) and the change (or delta) is then applied to the baseline (**Figure 15B**).

There are two ways to use the method, namely by calculating a mean (**Figure 15A**) change over the entire distribution of observations or by using the corresponding quantiles of the distribution (see Gennaretti, Sangelantoni and Grenier, (2015) for an example of quantile mapping technique). The latter allows for the application of a different correction factor to the distribution tails, making it possible to change the extremes of the distribution differently than the rest of the distribution. An important point here is that this technique is applied to specific time horizons (such as 30-year periods), not to the entire time series.

Absolute delta (addition/subtraction) is typically used for variables that do not have a true zero (e.g. temperature). Relative delta (ratio) is typically used for variables that have a true zero (e.g. precipitation).

The mean change or the quantiles (i.e. the probability distribution function) can be computed at the annual, seasonal, monthly or daily scale. Typically, a mean annual change will be applied on mean annual values and so on.

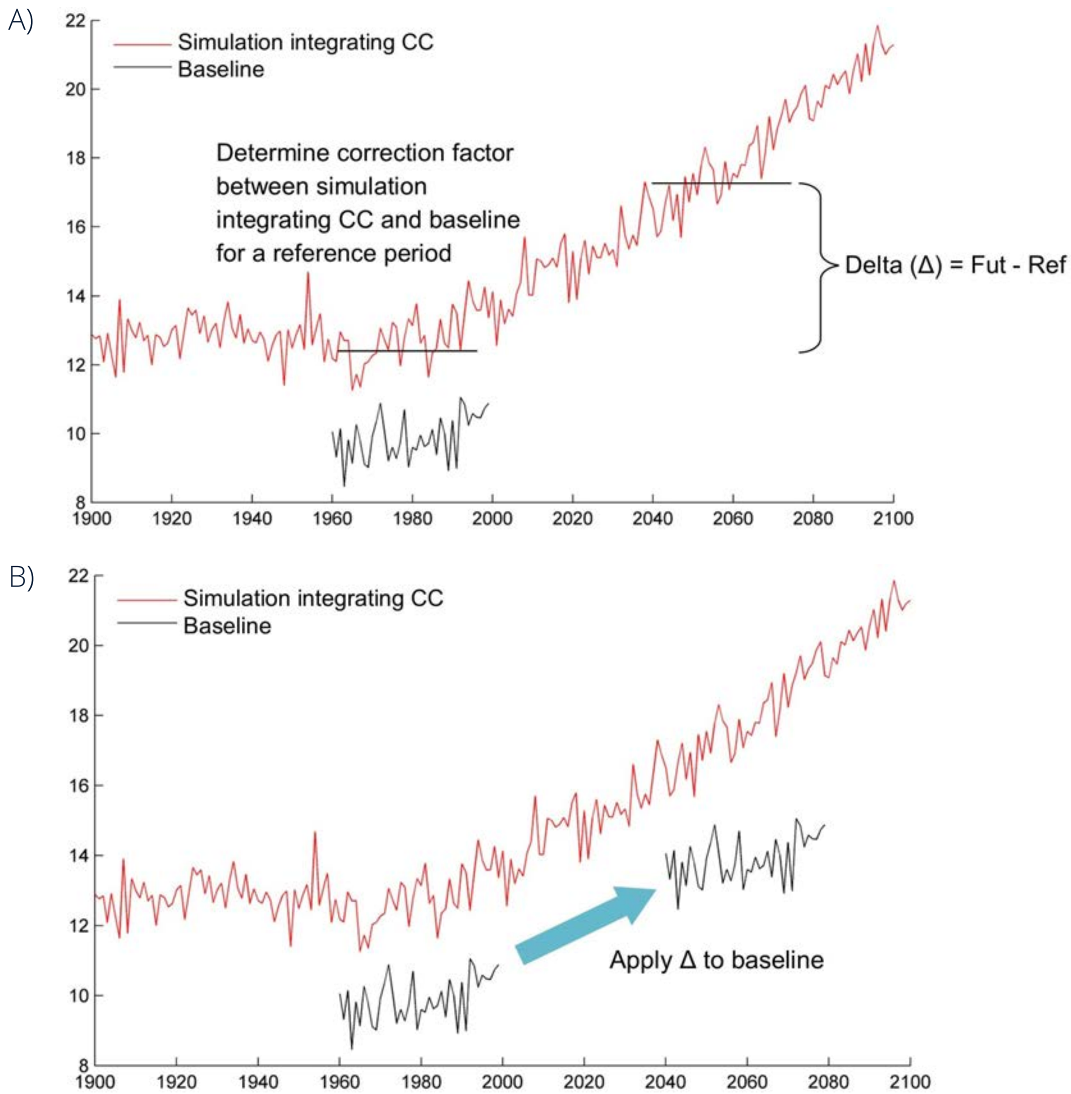


Figure 15 Example of delta method by calculating the mean. The relative change between the simulation in the reference period and in the future is first calculated (Panel A). The change is then applied to the baseline (Panel B) (adapted from Charron, 2016).

3.5.1. Advantages of the delta method

- Simple when calculating a mean change over the entire distribution of observations. This method is simple because a single factor is calculated and it is simply added to the observations over specific (e.g. 30-year) time horizons.
- Average complexity when using the corresponding quantiles of the distribution. This method is moderately complex, because it requires a comparison of distributions (i.e. probability distribution functions). Nonetheless, distributions are obtained over specific time horizons (e.g. 30-year), which simplifies the process.
- It enables the comparison of past years with a similar future year with climate change. It also maintains the sequence of events, which can be of particular interest when comparing the past with the future (Snover et al., 2003).

3.5.2. Disadvantages of the delta method

- Errors in the baseline, trends, cycles, step and abrupt changes and influences from past drivers are projected into the future and transmitted to the next step in the modelling chain.
- Some temporal information may be missing in the final result. For example, in **Figure 15**, the years 2000 to 2040 are missing.
- This method modifies the means or the quantiles of the baseline (or simulation based on the baseline). All other information contained in the simulation integrating climate change, such as modification to sequence of dry and wet days or length of dry spells, are not used in the scenario.
- Potential future step changes (abrupt changes) are ignored.

3.6. Bias correction method

Bias correction is described by Charron (2016) for climate data. The definition is generalized below to suit the needs of the modeling chain.

This method involves an adjustment or correction of the entire simulation integrating climate change using a bias or correction factor such that differences between the simulated reference period data and the baseline values are reduced. The correction factor is first calculated by comparing the simulated reference period and the baseline values over the same time period, such as 1961–1990 (**Figure 16A**). The correction is then applied to the entire simulation integrating climate change (**Figure 16B**). As for the perturbation method, a bias correction can be based on a mean correction or on quantiles. However, unlike the delta method where the correction is done for a given time horizon, this method allows for the bias to be removed from the entire simulation integrating climate change.

Absolute correction factor (addition/subtraction) is typically used for variables that do not have a true zero (e.g. temperature). Relative correction factor (ratio) is typically used for variables that have a true zero (e.g. precipitation).

As with the delta method, the mean change or the quantiles can be computed at the annual, seasonal, monthly or daily scale. Typically, a mean annual change will be applied on mean annual values and so on.

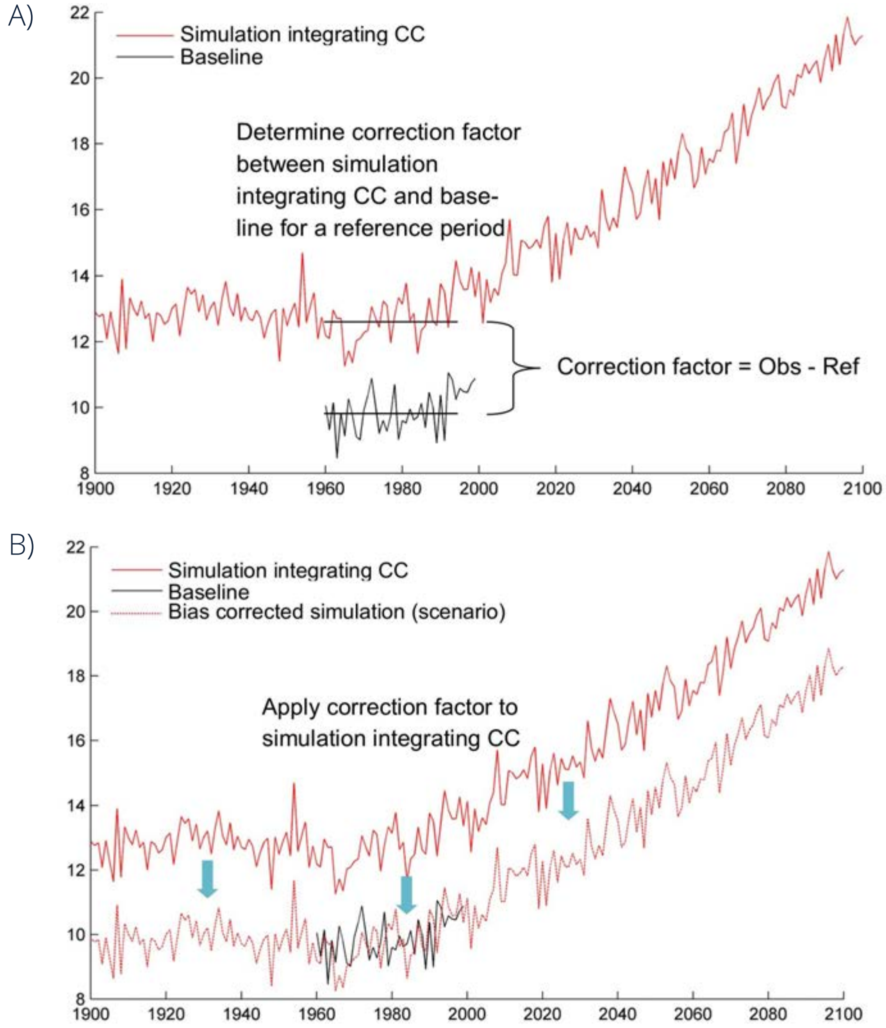


Figure 16 Example of bias correction method. The relative change between the simulated reference period and the baseline values is first calculated (Panel A) and the change is then applied to the simulation time series (Panel B) (adapted from Charron, 2016).

3.6.1. Advantages of bias correction method

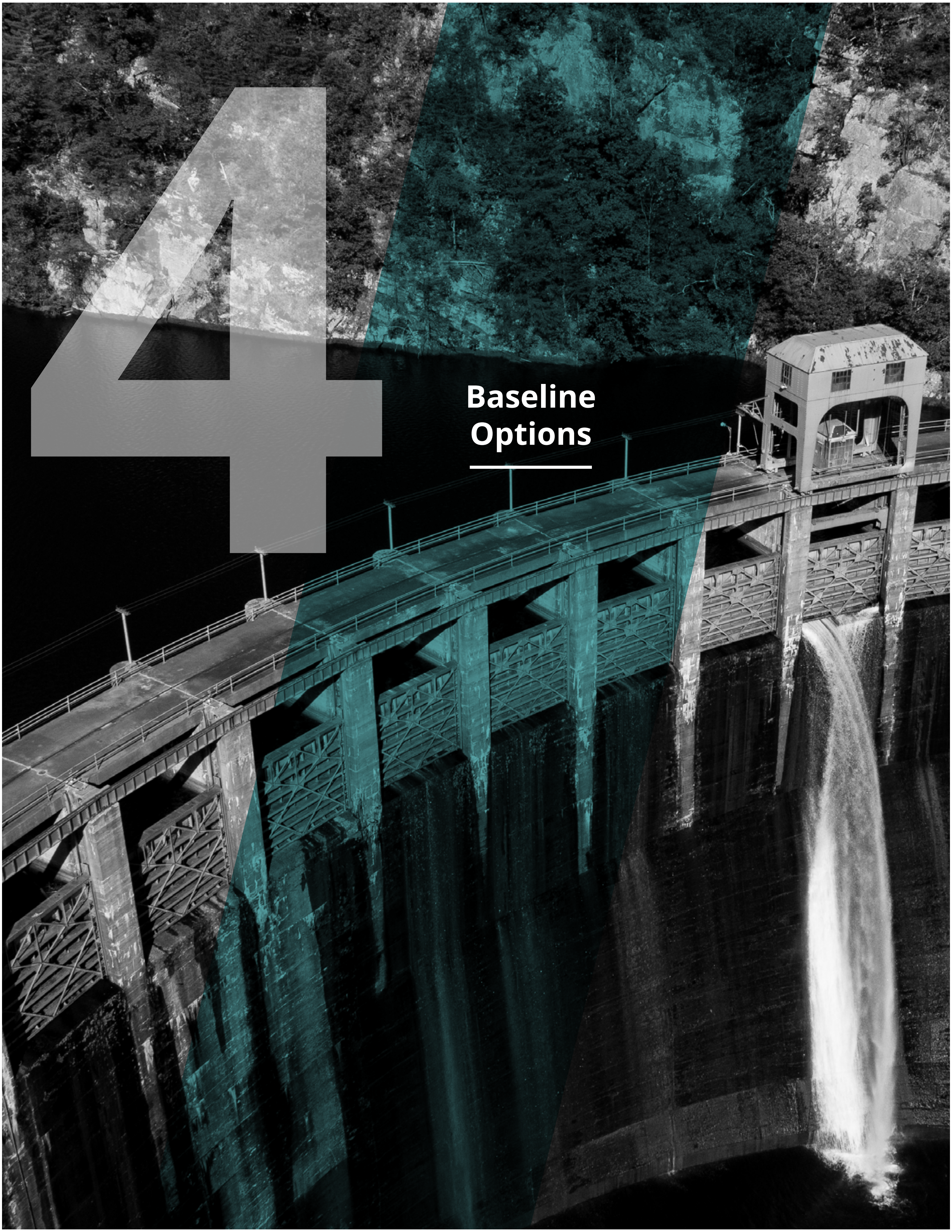
- Simplicity: calculate a single factor and add it to the observations over specific time horizons (e.g. 30 years).
- Because the simulation is modified to match the observations (rather than the observations modified to match the simulation), all other information contained in the simulation integrating climate change, such as modification to sequence of dry and wet days or length of dry spells, is retained.
- With this method, it is possible to use several simulations integrating climate change, and thus get many different realizations or sequences of events.
- The method yields continuous results in time rather than results over specific time horizons (e.g. 30 years).

3.6.2. Disadvantages of bias correction method

- Method of greater complexity when using the corresponding quantiles of the distribution. This method is highly complex, because it requires a comparison of distributions (i.e. probability distribution functions). Moreover, the changes are applied to the entire simulation, which complicates the process.
- Weaknesses in the simulation not corrected by bias correction (i.e. unrepresentative sequences of events) are transmitted to the next step in the modeling chain.
- This method does not maintain the historical sequence of events, preventing direct comparison between the past and the future, as in the delta method.

4

Baseline Options



This section reviews important concepts about selecting and developing a baseline. In this Guidebook, the baseline is the data that are judged to best represent the past or current state of a system. In the valuation method with climate change, it can be used in several ways: to produce simulations based on the baseline (the first set of simulations explained in **Section 2**), to perform data transformation methods and/or to calibrate hydrologic models.

Two types of baselines are suggested: the hydrologic baseline only; or a combination of the climatic and hydrologic baselines. In the latter case, both types of baselines are needed to at least calibrate and validate the hydrologic model.

- The climatic baseline, presented in **Section 4.1**, consists of historical data for precipitation, and minimum and maximum temperatures (and potentially other hydroclimate variables needed as input in the hydrologic model).
- The hydrologic baseline, presented in **Section 4.2**, consists of historical hydrology data.

Many criteria must be considered when selecting the baseline option. Among them, the most important are: the availability of a hydrologic model and a water management model; the minimum amount of time to perform the assessment; the cost and expertise required; and the desired level of control over the modeling chain. **Table 5** describes each selection criteria and **Figure 17** lists the specific requirements for each of the baseline option.

As **Figure 17** shows, when working with the climatic and hydrologic baseline, a hydrologic model is needed, and a water management model is potentially needed (the need for a water management model also depends on the upstream watershed of a dam, whether the inflows are regulated or naturalized). The assessment will take more than 3 months to realize, the cost and expertise needed are high and the level of control over the modeling chain is high.

If working with the hydrologic baseline only, a hydrologic model is potentially needed (it will also depend on the outcome of the analysis described in **Section 5**) and a water management model is also potentially needed. The assessment may take less than one month, the cost and expertise needed are average and the level of control over the modelling chain is average.

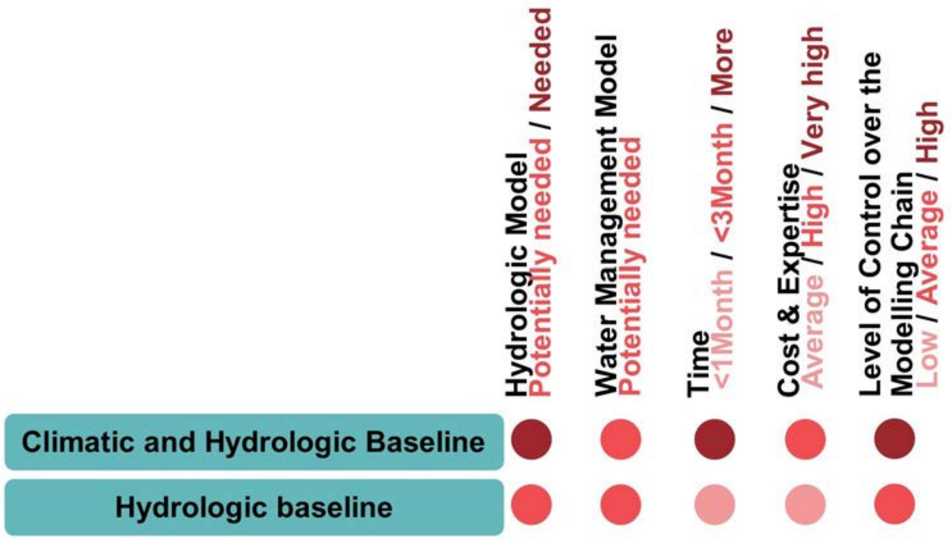


Figure 17 Overview of selection criteria for the type of baseline (see **Table 5** for definitions)

Table 5 Description of selection criteria for the type of baseline and for climate change data

Selection Criteria	Description
Hydrologic Model	The option requires that a hydrologic model be calibrated, validated and run to produce streamflow data; calibration of the hydrologic model requires a good set of climate information.
Water Management Model	The option requires a model that uses the inflow from the hydrologic model and includes a routine for routing water between sub-catchments and through reservoirs, dams and hydraulic structures. It provides explicit representation for decisions related to storing or releasing water. The options range from simple models following defined rule curves to advanced optimization routines that explicitly seek to maximize some criteria while respecting a series of constraints such as regulatory limits. They are sometimes embedded in hydrologic models and in energy models. This type of model is required to produce simulations with regulated streamflow and to represent flow in an actual regulated environment (see **Section 6.3.1** – Specific consideration: regulated vs. Naturalized).
Time	Estimation of the minimum amount of time required to implement the option.
Cost and Expertise	Estimation of the cost and expertise required to implement the option. **Section 4.1** – Climatic baseline and **4.2** – Hydrologic baseline provide more information about the kind of expertise needed.
Level of Control over the Modelling Chain	Estimation of the level of control over the modeling chain. Typically, the greater the control over the modeling chain, the more comprehensive the results.

WARNING ABOUT EXAMPLES OF RESOURCES

Note that each section includes examples of resources to help the practitioner carry out valuation exercises. None of these resources have been validated. Therefore, the practitioner should assess the adequacy of each resource before integrating it into the modeling chain.

4.1. Climatic baseline

The climatic baseline typically consists of historical data for precipitation, and minimum and maximum temperatures (and potentially other hydroclimate variables needed as hydrologic model inputs).

It is new to most organizations in the industry. It complies with the Hydropower Sector Climate Resilience Guide (IHA, 2019) and offers many advantages to those starting to work with climate change.

Historical data for climate can come from weather stations in the watershed, from gridded observations or from reanalysis. It is best to use the same coherent dataset for all variables. A single dataset is consistent in time and space; using data from different datasets can produce inconsistencies in the modeling chain.

The standard minimum time period to account for natural variability cycles is 30 years. A longer time period enables the capture of longer climatic cycles, such as those that occur in the Great Lakes Basin (Hanrahan et al., 2010), and is worth considering. The practitioner should note that the weather-gauge network density, and the quality of gridded-observed product and reanalysis might not be sufficient for the next step in the modeling chain. For more information, see the Box Climatic Drivers and Limitations of the Climatic Baseline.

A careful selection of the climatic baseline, consistent with the selection of the climate change data and data transformation methods, is also recommended, as it can avoid further inconsistencies in the modeling chain. For a discussion on this subject, see **Section 7.4** – Consistency of climatic data and time periods.

CLIMATIC DRIVERS AND LIMITATIONS OF THE CLIMATIC BASELINE

What are climatic drivers?

The climatic baseline incorporates natural variability, natural catastrophes and climate change all at the same time. These are the driving forces – the climatic drivers. Natural variability is the result of climate cycles such as El Niño and La Niña, which influence temperature and precipitation in the watershed and directly impact streamflow. Natural catastrophes, such as large volcanic eruptions, can also have significant impacts on a watershed, as they can temporarily decrease temperatures across the globe. Climate change, which is a change in long-term average of weather pattern, also has notable impacts on a watershed.

Errors, heterogeneities, bias and uncertainties

The quality of the climatic baseline for a watershed often depends on the density of its weather gauge network. For example, a low-density gauging network samples few points in space, and while it may detect intense confined storms, it may be bypassed entirely by a storm that impacts almost the entire watershed.

The climatic baseline is also prone to errors, heterogeneities, bias and uncertainties. Indeed, weather stations' data contain measurement errors and heterogeneities. Sometimes, the measurement instrument or its location changes, which can create breaks in datasets and suggest false trends in the time series.

Gridded observations and reanalyses are also prone to bias and uncertainties. For example, gridded observations, in addition of being dependent upon the density of its weather gauge network, can smooth out and diminish the peak of convective storms through areal averaging. Reanalyses merge models and observations, drawing on the strengths of each.

These limitations of the climatic baseline can become embedded in hydrologic simulations – and in the rest of the modeling chain – because of the hydrologic model and its calibration process. Through calibration, the model is tuned to provide adequate results, but the model becomes conditioned to some characteristics of the selected precipitation product.

4.1.1. Requirements for selecting the climatic baseline

- Available climatic and hydrologic datasets are suitable and cover a sufficiently long time period.
- A properly calibrated continuous hydrologic model (see **Appendix F** – Selection and calibration of a hydrologic model).
- If the upstream watershed is highly regulated (see **Section 6.3.1** – Specific consideration: regulated vs. naturalized), potentially a water management model.
- More than 3 months to complete the valuation process.
- Human resources with significant expertise in hydrology and average expertise in climate and climate change.

4.1.2. Why choose the climatic baseline?

- An organization is interested in getting a deeper understanding of the watershed hydrology.
- An organization is interested in the relative impact of climate change compared to the impacts of other hydrologic drivers.
- An organization is interested in following the methods laid out in the Hydropower Sector Climate Resilience Guide (IHA, 2019).

4.1.3. Advantages of the climatic baseline

- This option provides the most flexibility in terms of analyses. The practitioner is in a position to analyze and better understand every hydrologic driver (see **Section 4.2** – Hydrologic baseline). The following four methods can help increase the understanding of the relative importance of each hydrologic driver:
    - Force the hydrologic model with a stationary (non-changing) climatic scenario to understand natural variability.
    - Force the hydrologic model with different climatic scenarios to understand the impact of climate change on the recent past.
    - Force the hydrologic model with different land uses to understand the impacts of land-use changes in the recent past.
    - Force the water management model with different operation rules to understand the impacts of regulatory changes in the recent past.
- The practitioner can use a water management model to make the future scenario more consistent with the baseline (see **Section 7.8** – Benefits of hydrologic and water management modeling).
- With this type of baseline, the literature research is facilitated as more information exists about future regional climate (e.g. temperature and precipitation) than about future regional hydrology (e.g. streamflow) (see **Section 5**).
- There are fewer sources of non-stationarity (changes over time) in the climate record than in the hydrologic record. Therefore, it can be easier to adjust a climatic baseline than a hydrologic baseline (see **Section 6.3** – From hydrology to energy).

4.1.4. Disadvantages of the climatic baseline

- Relying on a hydrologic simulation based on the climatic baseline (reconstructed hydrology) implies a very strong hypothesis that the model performs adequately to represent the hydrology of the watershed. Even small biases in the hydrologic simulation based on the climatic baseline can result in serious implications for energy modeling performed later in the modeling chain. This hypothesis can be verified using the steps provided in **Appendix G** – Validation of hydrologic simulations.
- For watersheds affected by upstream regulation, a water management model might be unable to reproduce the regulation characteristics because of a lack of data/knowledge about the dams upstream (e.g. dams are in a different country) or because of the complexity of the regulation. In this case, the hydrologic simulation based on the climatic baseline might be problematic in the rest of the modeling chain. An alternative could be to work at a coarser time scale (see **Section 7.7** – Model scaling).

4.1.5. Next steps

a) Assess the adequacy of climatic baseline (see **Appendix E** – Validation of climate products).

b) Carry out detection and attribution study if needed (see **Appendix B** – Detection and attribution in the context of climate change)

c) Apply data transformation if needed (see **Section 6.2** – From climate to hydrology).

d) Select and calibrate hydrologic model (see **Appendix F** – Selection and calibration of a hydrologic model).

e) Run hydrologic simulation based on climatic baseline.

f) Assess adequacy of hydrologic simulation based on climatic baseline (see **Appendix G** – Validation of hydrologic simulations).

g) Carry out sensitivity analysis with the modeling chain (see **Appendix H** – Sensitivity Analysis)

h) Go to **Section 5**.

4.1.6. Examples of resources for the climatic baseline

Gridded observation

NRCan Canada Daily Gridded product – Natural Resources Canada
https://cfs.nrcan.gc.ca/projects/3/4

Livneh gridded precipitation and other meteorological variables for continental US, Mexico and Southern Canada – National Center for Atmospheric Research (NCAR)
https://climatedataguide.ucar.edu/

Daymet – NASA
https://daymet.ornl.gov/

Daily Gridded Meteorological Datasets – Pacific Climate Impacts Consortium (PCIC)
https://data.pacificclimate.org/portal/gridded_observations/map/

Prism Recent Past – PRISM Climate Group
http://prism.oregonstate.edu/

Climatic Research Unit Time-Series (CRU TS) – Climatic Research Unit (CRU)
https://crudata.uea.ac.uk/cru/data/hrg/

Reanalysis

The European Centre for Medium-Range Weather Forecasts 5th generation reanalysis (ERA5) – European Centre for Medium-Range Weather Forecasts (ECMWF)
https://www.ecmwf.int/en/forecasts/datasets/reanalysis-datasets/era5

ERA5-Land – European Centre for Medium-Range Weather Forecasts (ECMWF)
https://www.ecmwf.int/en/era5-land

Climate Forecast System Reanalysis (CFSR) – National Centers for Environmental Prediction (NCEP)
https://climatedataguide.ucar.edu/climate-data/climate-forecast-system-reanalysis-cfsr

WATCH-Forcing-Data-ERA-Interim – Water and Global Change (WATCH)
http://www.eu-watch.org/data_availability

Modern-Era Retrospective analysis for Research and Applications (MERRA) – NASA
https://gmao.gsfc.nasa.gov/reanalysis/MERRA/

Modern-Era Retrospective analysis for Research and Applications, Version 2 (MERRA-2) – NASA
https://gmao.gsfc.nasa.gov/reanalysis/MERRA-2/

AgMERRA – NASA
https://data.giss.nasa.gov/impacts/agmipcf/agmerra/

North American Regional Reanalysis (NARR) – National Centers for Environmental Information (NOAA)
https://www.ncdc.noaa.gov/data-access/model-data/model-datasets/north-american-regional-reanalysis-narr

JRA55 – National Center for Atmospheric Research (NCAR)
https://climatedataguide.ucar.edu/climate-data/jra-55

Mixed products

Multi-Source Weighted-Ensemble Precipitation (MSWEP) – Princeton University
http://www.gloh2o.org/

Global Meteorological Forcing Dataset for land surface modelling (GMFD) – Princeton University
http://hydrology.princeton.edu/data.pgf.php

WFDEI-GEM-CaPA – Federated Research Data Repository
https://www.frdr-dfdr.ca/repo/handle/doi:10.20383/101.0111

4.2. Hydrologic baseline

The hydrologic baseline consists of historical hydrology data and corresponds with the baseline most organizations typically use to value assets (see **Section 2.1** – Traditional valuation method).

Historical hydrology data can come from streamflow observations: of nearby sites; transposed from another site; from regionalization techniques (Razavi and Coulibaly, 2013); or from a reconstruction by water balance (reconstruction of inflows in a reservoir based on the changes of level and other variables).

As with the climatic baseline, it is recommended to use a minimum of 30 years worth of data. Using a longer period is also worth considering (see **Section 4.1** – Climatic baseline).

Historic flow measurements are influenced not only by climate, but also by other factors such as changes in instrumentation (e.g. type of flow gauge), changes at the watershed level (such as changes in land use), etc. This means that climate change trends in the streamflow record can be exacerbated, neutralized or reversed by other driving forces. Therefore, it is important to have a strong understanding of the factors influencing the flow record when working with climate change (see the Box Hydrologic Drivers and Limitations of the Hydrologic Baseline).

HYDROLOGIC DRIVERS AND LIMITATIONS OF THE HYDROLOGIC BASELINE

What are hydrologic drivers?

The climatic baseline and the hydrologic baseline both incorporate natural variability, natural catastrophes and climate change. Indeed, when the temperature and precipitation over a watershed are influenced, the streamflow is directly impacted. Other factors impact only the hydrologic baseline. These include land-use changes, such as urbanization, deforestation and wildfires, as they can significantly modify hydrologic processes such as infiltration capacity and evapotranspiration. Finally, the hydrologic baseline also incorporates changes in the regulation of upstream reservoirs and hydraulic structures, such as construction or refurbishment of hydraulic structures or adjustments changes in the regulation of existing structures. All of these are driving forces of the hydrologic baseline – the hydrologic drivers. They all act simultaneously on the amount and timing of inflows.

Errors, heterogeneities, bias and uncertainties

Like the climatic baseline, the hydrologic baseline is also prone to errors, heterogeneities, bias and uncertainties. Streamflow observations are subject to measurement errors and uncertainties due to instrument uncertainty, measurement conditions, uncertainties of rating curves and their evolution over time (Horner et al., 2018). These also contain heterogeneities when the measurement instrument or its location changes. The heterogeneities can create breaks and/or false trends in the time series. Streamflow observations from another site or transposed from another site are additionally impacted by the uncertainty of the transposition method. Similarly, streamflow reconstruction from water balance will contain uncertainties due to the reconstruction method.

4.2.1. Requirements for selecting the hydrologic baseline

- Access to a suitable hydrology dataset covering a sufficiently lengthy time period
- Average expertise in hydrology, climate and climate change

4.2.2. Why choose the hydrologic baseline?

- An organization is looking at climate change for the first time and wants to assess the level of effort required.
- The organization has time (less than one month) and resource constraints. Note that developing a hydrologic baseline may take longer than one month depending on the size of the watershed, the availability of the data and other factors.
- A continuous hydrologic model for the watershed is not available. This could be because the organization has either not identified needs that warrant its development, or is in the process of developing it.
- The inflows for the dam of interest come from a highly regulated watershed (see **Section 6.3.1** –Specific consideration: regulated vs. naturalized). Very few data are available to properly model the upstream watershed regulation.
- There are no meteorological stations in or near the watershed of interest, which make the use of the climatic baseline more difficult.
- The length of the hydrologic record is longer than the length of the meteorological record (see **Section 4.1** – Climatic baseline).
- The organization's internal processes and planning assumptions are strongly linked to an existing hydrologic baseline.

4.2.3. Advantages of the hydrologic baseline

- As the hydrologic baseline is often used in the industry for asset valuation, its use to evaluate the impacts of climate change could be more acceptable in the organization. It provides a high level of continuity with former analyses of the hydroelectric system.
- The hydrologic record of a watershed integrates the hydrologic drivers for large spatial domains (e.g. climate and land cover).

4.2.4. Disadvantages of the hydrologic baseline

- The hydrologic baseline has many sources of non-stationarity (i.e. hydrologic drivers that cause changes over time). The practitioner might not always have a deep understanding of processes underway in the watershed.

4.2.5. Next steps

a) Apply data transformation if needed (see **Section 6.3** – From hydrology to energy)

b) Carry out sensitivity with the modeling chain (see **Appendix H** – Sensitivity Analysis)

c) Go to **Section 5**.

4.2.6. Examples of resources for the hydrologic baseline

Historical Hydrometric Data – Government of Canada
https://wateroffice.ec.gc.ca/mainmenu/historical_data_index_e.html

National Water Information System – United States Geological Survey (USGS)
https://waterdata.usgs.gov/nwis

Water Level and Flow Rates – Government of Quebec
https://www.cehq.gouv.qc.ca/hydrometrie/index-en.htm

5

Options for Climate Change Data

This section provides an overview of the different types and sources of data that the practitioner can use to represent climate change conditions. The climate change data can be used to produce simulations integrating climate change (the second set of simulations explained in **Section 2**) and/or to perform data transformation methods.

All of these options are based on emissions scenarios and climate models. For example, the practitioner can work with raw climatic simulations (direct output from climate models) from the CMIP experiments. This option offers many advantages, but involves a lot of work and requires specific expertise to produce a credible end result. Another option is to rely on the expertise of governmental organizations, climate centers, universities, engineering firms, consultants, etc., which may have carried out a lot the work already. It might conserve time and money, and provide robust results.

Section 5.1 through **5.7** present the various types and sources of data. Before going further, consult the Box Warning about examples of resources in **Section 4**.

When selecting climate change data, many criteria must be considered. The main ones are the same as for the baseline: availability of a hydrologic model and a water management model; minimum amount of time needed to perform the assessment; cost and expertise required; and desired level of control over the modeling chain. **Table 5** describes each selection criteria and **Figure 18** lists the specific requirements for each of the climate change data options.

As shown in **Figure 18**, when working with pre-computed results from climatic simulations, a hydrologic model is needed, and a water management model is potentially needed (the need for a water management model also depends on the upstream watershed of a dam, whether the inflows are regulated or naturalized). The assessment can take less than 3 months to complete, the cost and expertise needed are high, and the level of control over the modelling chain is average.

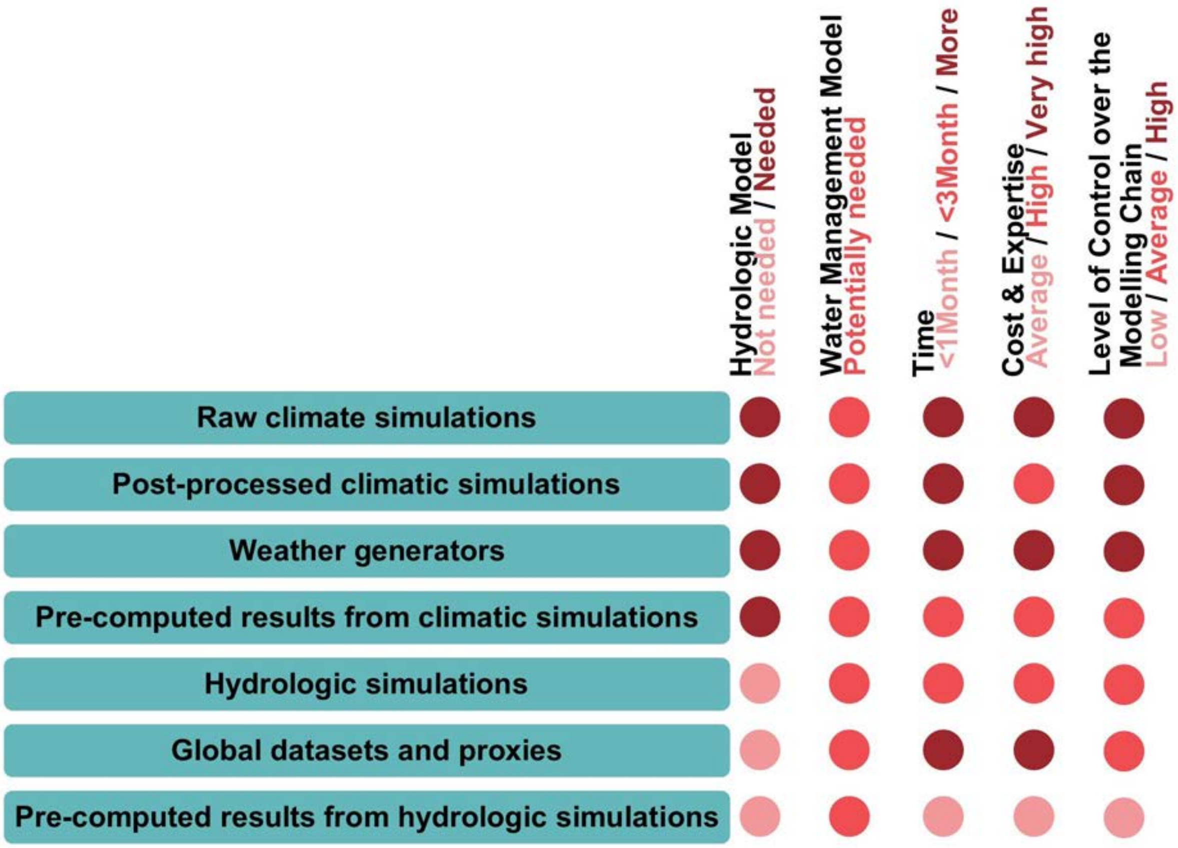


Figure 18 Overview of selection criteria for the type of climate change data (see **Table 5** for definitions)

5.1. Raw climatic simulations

Most raw climatic simulations from either GCMS or RCMs are publicly available. Precipitation, along with minimum and maximum temperatures, are typically of interest for hydrologic modeling, although other variables such as wind and solar radiation are more commonly included in recent years to assess evapotranspiration using more complex formulae. The time step of the data may vary from sub-daily to monthly. The spatial resolution of the data typically varies by model: from a grid of 10 to 45 kilometers for RCMs, and from 90 to 350 kilometers for GCMs. Also, calendars within RCM and GCM do not necessarily follow the Gregorian calendar (some GCM exclude leap years and others use a 360-day year).

RESOLUTION, BIASES AND EXTRACTION OF RAW CLIMATIC SIMULATIONS

Despite coarse resolution and biases, raw climatic simulations data are still usable. However, additional manipulations must be made on the data before their integration in the modeling chain. Downscaling methods can be undertaken to deal with coarse resolution (see Charron (2016) and Maraun and Widmann (2018)). The delta method (**Section 3.5**) or bias correction method (**Section 3.6**) can be undertaken to correct biases.

Downloading these datasets and extracting the relevant variables can be a long and tricky process. The datasets are on international public servers (e.g. Earth System Grid Federation (ESGF) nodes), in a format not familiar to most water-resources managers (e.g. NetCDF files) and their size is often large (multiple gigabytes per variable per year). Climate-service providers tend to have the skills to deal with these situations and can be of a great help.

5.1.1. Requirements for selecting raw climatic simulations

- Good-quality climatic and hydrologic baselines
- A properly calibrated continuous hydrologic model
- If the upstream watershed is highly regulated (see **6.3.1** – Specific consideration: regulated vs. naturalized), potentially a water management model.
- More than 3 months to complete the valuation process
- Strong expertise in hydrology, climate and climate change, and strong programming skills (raw climatic simulations are gridded products in NetCDF files format)

5.1.2. Why choose raw climatic simulations?

- The business activity needs detailed information (examples: risk analysis, late stage of project development, refurbishment, etc.).
- There is no readily available, well performing and robust dataset (e.g. post-processed climatic simulations (**Section 5.2**) or hydrologic simulations (**Section 5.5**) for the watershed of interest).
- Conducting in-house post-processing, data transformation method for further use in the modelling chain, can be an improvement over existing post-processed products (e.g. high-quality data are available from private climate stations and are not used in existing post-processed products).
- The practitioner wants to explore a very specific question and the climate ensemble is not already downscaled and bias-corrected.

5.1.3. Advantages of raw climatic simulations

- The organization has complete control over the modeling chain.
- Supports the production of several simulations to represent rare events.

5.1.4. Disadvantages of raw climatic simulations

- Complexity
- Considerable time and expertise are required for post-processing of the raw simulations. For newcomers, the learning curve to deal with raw climate data is steep.

5.1.5. Next steps

a) Make sure to choose both a climatic and hydrologic baseline (see **Section 4**).

b) Follow guidance provided in **Appendix I** – Best and good practices for the ensemble approach.

c) Make GCMs selection, if needed (see **Appendix C** – GCM selection methods).

d) Go to **Section 6.2** – From climate to hydrology.

5.1.6. Examples of resources for raw climatic simulations

CMIP – World Climate Research Programme
https://www.wcrp-climate.org/wgcm-cmip

Coordinated Regional Climate Downscaling Experiment (CORDEX) –
World Climate Research Programme
https://www.cordex.org/

Dynamically-downscaled climate projections – Climate Change Data Portal
http://ccdp.network/

Climate Change Knowledge Portal – World Bank Group
https://climateknowledgeportal.worldbank.org/download-data

UKCP18 – Met Office
https://www.metoffice.gov.uk/research/approach/collaboration/ukcp/about

5.2. Post-processed climatic simulations

Post-processed (downscaled and bias-corrected) climatic simulations ready for direct input into the hydrologic model are also available. Indeed, many climate centers publish datasets of this type; the practitioner can also partner directly with a climate center to obtain these.

A dataset with the appropriate input for the hydrologic model (typically precipitation, minimum and maximum temperatures) is required. Some of these datasets are available for many RCPs and GCMs at a resolution of 10 kilometers on a coherent grid at a daily resolution.

ADEQUACY OF POST-PROCESSED CLIMATIC SIMULATIONS

Downscaled and bias-corrected climatic simulations are still not perfect representations of the climate. These techniques will correct only certain aspects of the raw climatic simulations. Before using them in the modeling chain, be sure to carefully evaluate their adequacy and limitations (Appendix E – Validation of climate products).

5.2.1. Requirements for selecting post-processed climatic simulations

- An adequate dataset (see examples of resources below and next steps), because downscaled and bias corrected climate projections are not readily available.
- Good-quality climatic and hydrologic baselines
- A properly calibrated continuous hydrologic model
- If the upstream watershed is highly regulated (see **Section 6.3.1** – Specific consideration: regulated vs. naturalized), potentially a water management model
- More than 3 months to complete the valuation process
- Significant expertise in hydrology, climate and climate change, and significant programming skills (post-processed climatic simulations are gridded products in NetCDF files format)

5.2.2. Why choose post-processed climatic simulations?

- The business activity needs detailed information (examples: risk analysis, late stage of project development, refurbishment, etc.).
- Considerable savings of time and resources compared to using raw simulations if an adequate dataset is available for the watershed of interest.

5.2.3. Advantages of post-processed climatic simulations

- The organization has good control over the modeling chain.
- Post-processed datasets may have been created with more advanced post-processing techniques than in-house capabilities.

5.2.4. Disadvantages of post-processed climatic simulations

- The documentation of the datasets is not always clear and the limits of use are not well defined.
- The practitioner may lack confidence in externally produced data.
- Post-processing over large areas (e.g. across Canada) is typically done with interpolated or reanalysis datasets, which vary in skill depending on the location.

5.2.5. Next steps

a) Make sure to choose both a climatic and hydrologic baseline (see **Section 4**).

b) Follow guidance provided in **Appendix I** – Best and good practices for the ensemble approach.

c) Evaluate transferability of data and results, if needed (see **Appendix D** – Transferability of data and results)

d) Assess the adequacy of the climatic simulations (see **Appendix E** – Validation of climate products).

e) Go to **Section 6.2** – From climate to hydrology.

5.2.6. Examples of resources for post-processed climatic simulations

Earth Exchange Global Daily Downscaled Projections (NEX-GDDP) – NASA
https://cds.nccs.nasa.gov/nex-gddp/

Coordinated Regional Climate Downscaling Experiment (CORDEX) – World Climate Research Programme
http://www.cordex.org/data-access/bias-adjusted-rcm-data/

The Inter-Sectoral Impact Model Intercomparison Project (ISIMIP)
https://www.isimip.org/

Standard scenarios v1.0 – Ouranos
Project Under Development – Website coming soon!

Statistically downscaled climate scenarios – Pacific Climate Impacts Consortium
https://pacificclimate.org/data/statistically-downscaled-climate-scenarios

Projections for Australia's NRM's Regions – Climate change In Australia
https://www.climatechangeinaustralia.gov.au/en/climate-projections/explore-data/about-data/data-availability/

Dynamically-downscaled climate projections – Climate Change Data Portal
http://ccdp.network/

Spatial Downscaling Data – Climate change, agriculture and Food security (CCAFS)
http://www.ccafs-climate.org/data_spatial_downscaling/

5.3. Weather generators

A weather generator is a numerical model that produces synthetic climatic simulations based on the statistical characteristics of observed weather. Commercial versions are available, or the practitioner can develop one independently. The weather generator can either produce a stationary climate or be directly informed by trends from GCMs.

ADEQUACY OF CLIMATIC SIMULATIONS PRODUCED BY WEATHER GENERATORS

The adequacy/quality of climatic simulations produced by weather generators ranges from poor to good. Further, implementation of weather generators in studies of climate change impacts is less common than the use of climatic simulations from GCMs accompanied by the appropriate data transformation methods due to their statistical, rather than physical, basis.

Also, few commercial weather generators adequately maintain the spatial coherency of the weather between several sub-watersheds simultaneously.

5.3.1. Requirements for selecting weather generators

- Good-quality climatic and hydrologic baselines
- A properly calibrated continuous hydrologic model
- If the upstream watershed is highly regulated (see Section 6.3.1 – Specific consideration: regulated vs. naturalized), potentially a water management model.
- More than 3 months to complete the valuation process.
- Significant expertise in hydrology, climate and climate change, strong expertise in statistics, and significant programming skills.

5.3.2. Why choose weather generators?

- The business activity needs detailed information (examples: risk analysis, late stage of project development, refurbishment, etc.).
- To produce many simulations and recreate rare events.

5.3.3. Advantages of weather generators

- Good control over the modeling chain
- Generated time series conserve some key statistical parameters (e.g. length of wet and dry spells; Hayhoe, 2000).

5.3.4. Disadvantages of weather generators

- Complexity
- The development of weather generators that are adequate for hydrology, particularly if they necessitate multiple variables at multiple sites, is a challenging and lengthy task that few statisticians can accomplish. There are, however, a few successful examples (e.g. Abbasnezhadi, 2017).
- Procedure is entirely statistical (Wilks and Wilby, 1999).
- Quality of the output can be limited by the ability of the statistical model to produce a satisfactory fit (Wilks and Wilby, 1999).

5.3.5. Next steps

a) Make sure to choose both a climatic and hydrologic baseline (see **Section 4**).

b) Follow guidance provided in **Appendix I** – Best and good practices for the ensemble approach.

c) Evaluate transferability of data and results, if needed (see **Appendix D** – Transferability of data and results)

d) Assess the adequacy of the climatic simulations (see **Appendix E** – Validation of climate products).

e) Go to **Section 6.2** – From climate to hydrology.

5.3.6. Examples of resources for weather generators

KnnCAD Version 4 – University of Western Ontario
(King et al., 2014)

Multi-site stochastic weather generator (MulGETS) – Matlab
https://www.mathworks.com/matlabcentral/fileexchange/47537-multi-site-stochstic-weather-generator-mulgets
*** Integration of multi-annual cycles: (Chen et al., 2019)

OSSE-based algorithm – University of Manitoba
(Abbasnezhadi, 2017)

5.4. Pre-computed results from climatic simulations

Pre-computed results from climatic simulations can be found on websites, data portals, reports and scientific articles. Relevant information includes mean temperature and precipitation levels at the monthly, seasonal or annual scale for various time horizons (present and future to apply the delta method on the climatic baseline). Information about trends for these climate variables is also relevant (to apply an extension to the climatic baseline), and may be presented as maps, tables, figures, etc.

5.4.1. Requirements for selecting pre-computed results from climatic simulations

- Relevant results for at least the same time period as the climatic baseline and for a future period of interest (see Examples of resources and next steps).
- Good-quality climatic and hydrologic baselines
- A properly calibrated continuous hydrologic model
- If the upstream watershed is highly regulated (see **Section 6.3.1** – Specific consideration: regulated vs. naturalized), potentially a water management model.
- At least one month to complete the valuation process.
- Significant expertise in hydrology, and average expertise in climate and climate change

5.4.2. Why choose pre-computed results from climatic simulations?

- An organization is starting to work with the climatic baseline, is perhaps looking at climate change for the first time and wants to assess how the level of effort required.

5.4.3. Advantages of pre-computed results from climatic simulations

- Minimal effort may lead to robust results.
- Regional information may be available if local data are limited.

5.4.4. Disadvantages of pre-computed results from climatic simulations

- The practitioner is limited to the amount and type of information that is available and may not be able to access the raw data used to create figures, tables and maps. This would limit the rest of the modeling chain to the least-comprehensive approach.
- The practitioner is mostly limited to the delta method.
- The information might not be available at the appropriate spatial/time scale or for the appropriate watershed.
- Several studies of the same watershed can yield different results, leading to confusion.

5.4.5. Next steps

a) Make sure to choose both a climatic and hydrologic baseline (see **Section 4**).

b) Follow guidance provided in **Appendix I** – Best and good practices for the ensemble approach.

c) Evaluate transferability of data and results if needed (see **Appendix D** – Transferability of data and results).

d) Go to **Section 6.2** – From climate to hydrology.

5.4.6. Examples of resources pre-computed results from climatic simulations

Atlas of Global and Regional Climatic simulations – IPCC
https://www.ipcc.ch/report/ar5/wg1/atlas-of-global-and-regional-climate-projections/

Climate Change Knowledge Portal – World Bank Group
https://climateknowledgeportal.worldbank.org/

Climate Data for a Resilient Canada – Environment and Climate Change Canada
https://climatedata.ca/

Climate Portraits – Ouranos
https://www.ouranos.ca/climateportraits/#/

Statistical DownScaling Model (SDSM) – Loughborough University
https://sdsm.org.uk/sdsmmain.html

LARS-WG – *Long Ashton Research Station*
https://www.researchgate.net/publication/268304865_LARS-WG_A_Stochastic_Weather_Generator_for_Use_in_Climate_Impact_Studies

CLImate GENerator (CLIGEN) – *USA ARS*
https://www.ars.usda.gov/midwest-area/west-lafayette-in/national-soil-erosion-research/docs/wepp/cligen/

CLIMGEN – UK Climatic Research Unit
https://crudata.uea.ac.uk/~timo/climgen/
http://modeling.bsyse.wsu.edu/rnelson/registration/ClimGen.htm

WeaGETS – Jie Chen
https://www.mathworks.com/matlabcentral/fileexchange/29136-stochastic-weather-generator-weagets

WGEN, GEM, agGEM – USDA
https://www.nrcs.usda.gov/wps/portal/nrcs/detailfull/?cid=stelprdb1043533

5.5. Hydrologic simulations

Datasets of hydrologic simulations integrating climate change are increasingly available. The development of downscaled and bias-corrected climatic simulations, the selection and calibration of hydrologic model, as well as the running of climatic simulations are already complete. The practitioner can therefore directly access hydrologic simulations for a particular watershed or neighboring watersheds. If no such dataset is available, some organizations and/or consultants can produce them.

LIMITATIONS OF HYDROLOGIC SIMULATIONS

Hydrologic simulations are imperfect representations of watershed hydrology. These imperfections are the limitations of the datasets and should be evaluated by the practitioner before integrating them into the modeling chain.

5.5.1. Requirements for selecting hydrologic simulations

- An adequate dataset (see Examples of resources and next steps), because hydrologic simulations are not readily available
- A good hydrologic baseline
- At least one month to complete the valuation process
- Significant expertise in hydrology and average expertise in climate and climate change

5.5.2. Why choose hydrologic simulations?

- Considerable savings of time and resources if an adequate dataset is available for the watershed of interest or for a nearby watershed
- A continuous hydrologic model for the watershed is not available. This could be because the organization has either not identified needs that warrant its development, or is in the process of developing it.

5.5.3. Advantages of hydrologic simulations

- Hydrologic simulations integrating climate change are already computed for several RCPs, GCMs and sometimes several hydrologic models.

5.5.4. Disadvantages of hydrologic simulations

- The documentation of the datasets is not always clear, and the limits of use are not well defined.

- Limited ability to adapt the information for a specific purpose, as the practitioner did not calibrate the hydrologic model.
- The practitioner may lack confidence in externally produced data.

5.5.5. Next steps

a) Follow guidance provided in **Appendix I** – Best and good practices for the ensemble approach.

b) Evaluate transferability of data and results, if needed (see **Appendix D** – Transferability of data and results).

c) Go to **Section 6.2** – From climate to hydrology or **Section 6.3** – From hydrology to energy.

5.5.6. Examples of resources for hydrologic simulations

NAC2H:The North-American Climate Change and hydroclimatology dataset –
Richard Arsenault, François Brissette, Jie Chen
http://doi.org/10.17605/OSF.IO/S97CD

PAVICS-HYDRO – ÉTS and Ouranos
https://pavics-raven.readthedocs.io
Note: This resource does not directly provide hydrologic simulations, but can be used to produce them.

PAVICS-Data of Atlas hydroclimatique du Québec méridional
https://pavics.ouranos.ca/twitcher/ows/proxy/thredds/catalog/birdhouse/mddelcc/PROJECTIONS_HYDROCLIMATIQUES/catalog.html

Station hydrologic model output – Pacific Climate Impacts Consortium
https://pacificclimate.org/data/station-hydrologic-model-output

Gridded hydrologic model output – Pacific Climate Impacts Consortium
https://pacificclimate.org/data/gridded-hydrologic-model-output

Hydrologic Response of the Columbia River Basin to Climate Change – UW Hydro
https://www.hydro.washington.edu/CRCC/

Water quantity indicators for Europe – Copernicus
https://cds.climate.copernicus.eu/cdsapp#!/dataset/sis-water-quantity-swicca?tab=overview

Projected Changes in Streamflow – Skagit Climate Science Consortium
http://www.skagitclimatescience.org/projected-changes-in-streamflow/

5.6. Global datasets and proxies

Global hydrology datasets are increasingly available, and consist of hydrologic simulations created with global hydrologic model(s) fed by raw or downscaled and bias-corrected climatic simulations. Proxies consist of variables other than streamflow that can be modified to provide an idea of future streamflow behavior, such as the runoff variable of GCMs and RCMs.

RELEVANT INFORMATION ABOUT GLOBAL DATASETS AND PROXIES

Adequacy

The adequacy/quality of both global datasets and proxies range from poor to good at the spatial scale needed for most asset valuation. Their applicability still needs to be explored for use in the valuation of hydropower assets.

Runoff or streamflow?

- In a hydrologic model, the difference between runoff and streamflow is that the streamflow is routed to the outlet of a watershed. Runoff is distributed across the surface of the watershed, while streamflow is channelized (concentrated) and affected by hydraulics (e.g. flow restrictions).
- Some datasets include only the runoff, because the routing module requires costly computing time. The runoff can be used as a proxy (approximation) for streamflow, artificially routed to the outlet and transformed into streamflow by multiplying by the area of the watershed and doing the consequent unit change.
- When both the runoff and streamflow are available, streamflow is not necessarily a better option. It depends on the routing scheme in the model. As shown in **Figure 19**, the routing of the water in some hydrologic models does not correspond with reality (e.g. due to coarse resolution and issues in representing topography in models).
- The use of runoff and its transformation into streamflow is a valid approach when the concentration time of the watershed is of the same order of magnitude as the temporal resolution of the data.

Natural processes of interest?

These datasets do not systematically represent all natural processes; for example, climate models do not account properly for mountain glaciers (Randall et al., 2007). Furthermore, some climate models do not explicitly consider lateral hydrologic processes and surface heterogeneity (Davison et al., 2016). Practitioners interested in this option should first get a strong understanding of the dataset and validate its adequacy (**Appendix G** – Validation of hydrologic simulations).

Download and extraction

See the Box Resolution, biases and extraction of raw climatic simulations in **Section 5.1** – Raw climatic simulations.

For the extraction of runoff, it is a good practice to extract and consider all points in the watershed. The extraction of streamflow is a bit trickier because of the routing scheme. This step should be carried out carefully with the map of the routing scheme.

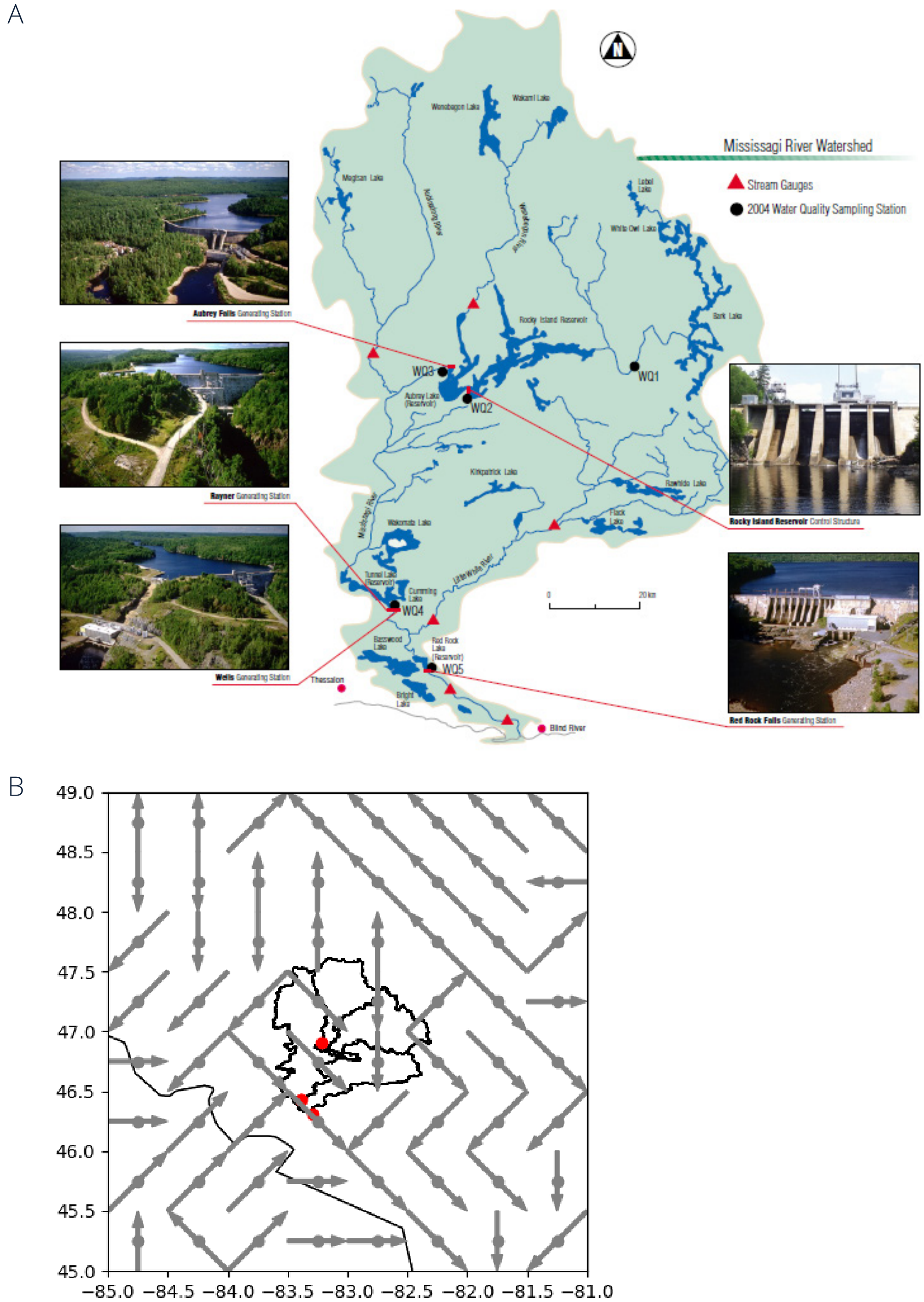


Figure 19 Example of the inconsistency between the real-world routing of water in a watershed and the routing scheme in a global hydrologic model. Panel A presents a map of the Mississagi watershed (produced by Hatch for Brookfield Renewable Power). In natural environments, flow is routed (directed) along the rivers. Panel B presents a map of the routing scheme in the ISIMIP ensemble. In models, flow routing is simplified; in this example, it is directed along the paths shown by the gray arrows, which are not representative of the actual streamflow routing due to their coarse resolution.

5.6.1. Requirements for selecting global datasets and proxies

- An adequate dataset with a spatial resolution of at least the same order of magnitude as the watershed of interest (see examples of resources and next steps)
- A good-quality hydrologic baseline
- A properly calibrated continuous hydrologic model
- More than 3 months to complete the valuation process
- Strong expertise in hydrology, climate and climate change, and strong programming skills (NetCDF files and gridded products)

5.6.2. Why choose global datasets and proxies?

- The use of a global hydrology dataset is appropriate when the watershed of interest is in a data-poor region (for meteorological and hydrologic observed data) (Krysanova et al., 2018).
- A continuous hydrologic model for the watershed is not available. This could be because the organization has either not identified needs that warrant its development, or is in the process of developing it. Furthermore, no sets of hydrologic simulations (as presented in **Section 5.5** – Hydrologic simulations) are available.
- An organization wants to raise awareness of climate change (Krysanova et al., 2018) and manipulate the data to produce tailored figures and graphs.
- The watershed is sufficiently large for coarser global datasets to provide adequate information about changes in the large-scale water balance.

5.6.3. Advantages of global datasets and proxies

- The hydrologic simulations integrating climate change are readily available for several RCPs, GCMs, and sometimes for several hydrologic models.
- The dataset potentially includes several scenarios of hydrologic drivers such as land cover and different water usages, etc.

5.6.4. Disadvantages of global datasets and proxies

- The documentation of the datasets is not always clear and the limits of use are not well defined.
- The practitioner may lack confidence in externally produced data.
- The datasets may not be well suited to the watershed of interest. The performance of such datasets range from excellent to poor, and vary by location and watershed scale (Krysanova et al., 2018). Thus, the global dataset and proxies option is usually less desirable than a calibrated hydrologic model, if available (**Section 5.5** – Hydrologic simulations).
- The dataset may be at a very low resolution, lower than the size of the watershed of interest.

5.6.5. Next steps

a) Follow guidance provided in **Appendix I** – Best and good practices for the ensemble approach.

b) Go to **Section 6.2** – From climate to hydrology or **Section 6.3** – From hydrology to energy.

5.6.6. Examples of resources for global datasets and proxies

CMIP5 – World Climate Research Programme
https://esgf-node.llnl.gov/projects/cmip5/

Coordinated Regional Climate Downscaling Experiment (CORDEX) –
World Climate Research Programme
https://www.cordex.org/

The Inter-Sectoral Impact Model Intercomparison Project (ISIMIP)
https://www.isimip.org/

5.7. Pre-com puted results from hydrologic simulations

Pre-computed results from hydrologic simulations can be found on websites, data portals, reports and scientific articles. Relevant information includes mean streamflow at the monthly, seasonal or annual scale for different time horizons (present and future to apply the delta method on the hydrologic baseline), as well as mean-streamflow trends (to apply an extension to the hydrologic baseline). This information may be presented in maps, tables, figures, etc. Table 6 shows an example of the type of information available in literature at the annual and seasonal scales.

Table 6 Example of hydrologic information found in the literature for rivers Chute-à-la-Savane and Passes-Dangeureuses. The table presents the annual and seasonal mean and standard deviation (Marie Minville et al., 2009).

	Mean (standard deviation) (mm)			
	Annual	Spring (AMJ)	Summer–autumn (JASON)	Winter (DJFM)
1961–1990	892 (103)	221 (45)	405 (57)	264 (49)
2010–2039	917 (109)	**235 (45)**	**391** (62)	**289 (63)**
2040–2069	**1,015** (102)	**256 (52)**	414 **(72)**	**344 (65)**
2070–2099	**1,107** (112)	**273 (65)**	**436 (74)**	**396 (67)**

Bold values indicate a statistically significant change compared to the control period

5.7.1. Requirements for selecting pre-computed results from hydrologic simulations

- Relevant results for at least the same time period as the climatic baseline and a future period of interest (see Examples of resources below and next steps)
- A good-quality hydrologic baseline
- Average expertise in hydrology, climate and climate change

5.7.2. Why choose pre-computed results from hydrologic simulations?

- An organization is looking at climate change for the first time and wants to assess how much effort to invest.
- The organization has little available time (less than one month) and resources.
- A continuous hydrologic model for the watershed is not available. This could be because the organization has either not identified needs that warrant its development, or is in the process of developing it.
- The organization carried out hydrologic simulations integrating climate change and wants to compare them with other studies.

5.7.3. Advantages of pre-computed results from hydrologic simulations

- Minimal effort may lead to robust results.
- Regional information may be available if local data are limited.

5.7.4. Disadvantages of pre-computed results from hydrologic simulations

- The practitioner is limited by the amount and type of available information. Also, the practitioner might not be able to access the raw data used to create figures, tables and maps. This can limit the rest of the modeling chain to the least-comprehensive approach.
- The information might not be available at the appropriate spatial/time scale or for the watershed of interest.
- Several studies of the same watershed can yield different results, leading to confusion.
- Impacts that are not correlated with mean annual inflows (such as extremes or step changes) are difficult to judge without the full data (time series).

5.7.5. Next steps

a) Follow guidance provided in **Appendix I** – Best and good practices for the ensemble approach.

b) Evaluate transferability of data and results if needed (see **Appendix D** – Transferability of data and results).

c) Go to **Section 6.2** – From climate to hydrology or **Section 6.3** – From hydrology to energy.

5.7.6. Examples of pre-computed results from hydrologic simulations

Hydroclimatic Atlas of Southern Quebec – Government of Quebec – Environnement et Lutte contre les changements climatiques
http://www.cehq.gouv.qc.ca/atlas-hydroclimatique/

Water quantity indicators for Europe – Copernicus
https://cds.climate.copernicus.eu/cdsapp#!/dataset/sis-water-quantity-swicca?tab=overview

6 Integration of the Baseline(s) and of Climate Change Data into the Modeling Chain

This section describes where to integrate the baseline(s) and climate change data into the modeling chain, as well as how to integrate them – by taking into account the specific challenges related to data transformation methods at each step of the modeling chain.

Section 6.1 starts with an explanation of the three types of integration (**Figure 20**). **Section 6.2**, **6.3** and **6.4**, respectively, cover each model intersection in the modeling chain: from climate to hydrology; from hydrology to energy; and from energy to value. **Section 6.5** provides two examples to illustrate the concepts presented and **Appendix J** - Case Studies provides four concrete examples of integration by different hydroelectric organizations.

6.1. Specific case of integration

Figure 20 illustrates three specific types of integration of the baseline climate change data into the modeling chain. The types differ according to baseline option (**Section 4**) and climate change data (**Section 5**). For each type, data transformation is possible at the beginning, as well as in between each model (see **Section 7.5.1** – Which one to apply and where?).

a) The climatic baseline and climate change data are fed into the hydrologic model with prior data transformation methods applied to them, if needed. Similarly, the hydrologic baseline is fed into the energy model with prior data transformation methods applied to it, if needed. This type of integration produces: a value simulation based on the climatic baseline; a value simulation based on the hydrologic baseline; and value simulations integrating climate change.

b) The climatic baseline is fed into the hydrologic model with prior data-transformation methods applied to it, if needed. The hydrologic baseline and the climate change data are fed to the energy model with prior data-transformation methods applied to them, if needed. The results of this type of integration are the same as type A.

c) There is no hydrologic model in the modeling chain. The hydrologic baseline and the climate change data are fed to the energy model with prior data-transformation methods applied to them, if needed. The results of this type of integration are: a value simulation based on the hydrologic baseline and value simulations integrating climate change.

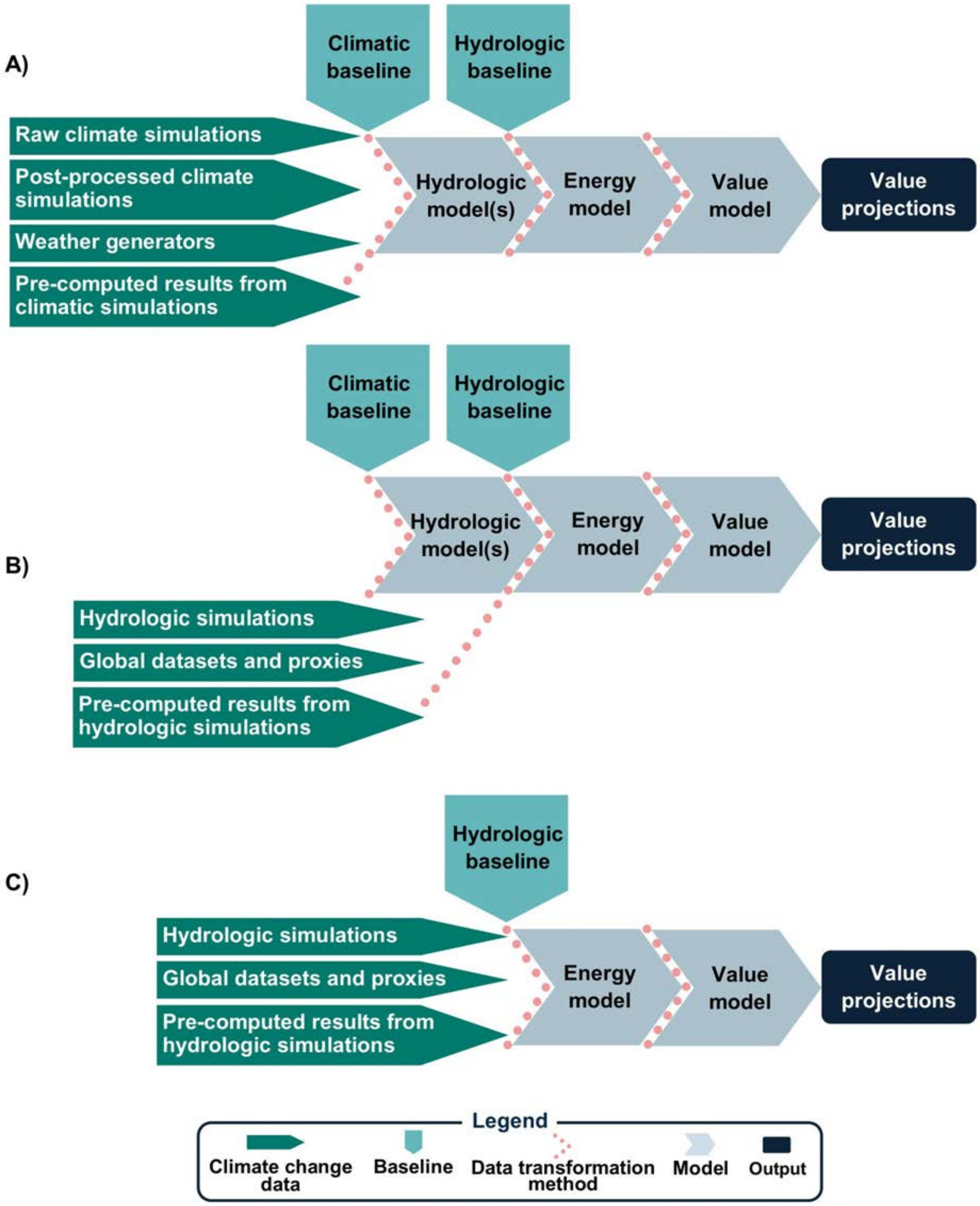


Figure 20 The three types of integration in the modelling chain according to type of baseline and climate change data. Panel A shows climate change data feeding the hydrologic model with prior data transformation methods applied to it if needed, using both climatic and hydrologic baselines. Panel B shows climate change data feeding the energy model with prior data transformation methods applied to it if needed, using both climatic and hydrologic baselines. Panel C shows climate change data feeding the energy model with prior data transformation methods applied to it if needed, using hydrologic baseline only.

6.2. From climate to hydrology

This section explains how to integrate the climatic baseline and the climate change data related to climate (Section 5.1 to 5.4) into the hydrologic model, as shown in Figure 20. It starts by presenting the most common and relevant types of data transformation methods for climatic simulations/results in Table 7. It then outlines specific considerations at this stage of the modeling chain (Section 6.2.1). Section 6.2.2 addresses specific considerations for the reduction and adjustment methods on the climatic baseline, while Section 6.2.3 through 6.2.5 address respectively the extension, the delta and bias correction methods. The direct method is not presented, as there are no specific considerations for its implementation. Also, note that advantages and disadvantages of each method are not repeated, as they appear in Section 3. Section 6.2.6 presents the next steps.

Table 7 presents the most common and relevant types of data transformation methods on the climatic baseline and on climate change data prior to their integration in the modelling chain at this stage. Refer to Section 3 for descriptions of the various methods: direct, reduction, adjustment, extension, delta and bias correction.

Table 7 Use of data transformation methods with the baseline and climate change data for the integration of climate data/results into a hydrologic model.

	Direct	Reduction	Adjustment	Extension	Delta	Bias correction
Climatic baseline	●	●	●	●	●	●
Raw climatic simulations				●	●	●
Post-processed climatic simulations	●			●	●*	
Weather generators	●			●		
Pre-computed results from climatic data				●	●	

*Consider this option if there are discrepancies between the climatic baseline from which the hydrologic model is calibrated and the raw climatic simulations that are post-processed (see Section 7.4 – Consistency of climatic data and time periods).

6.2.1. Specific consideration: Dataset coherence

At this stage, there are generally three variables under consideration: precipitation, and minimum and maximum temperature. It is recommended to feed the hydrologic model with the three variables from the same climatic simulation or climate product. A climate simulation/product is consistent in time and space, and using variables from different simulations in the hydrologic model produces physical inconsistencies.

6.2.2. Specific considerations for reduction and the adjustment of the baseline

Where climate change is known to influence the watershed, the reduction of a record longer than 30 years – for example the selection of the most recent 30-year period – can be most relevant, as the recent past better represents current conditions. However, other important information may be lost. See **Section 3.2** – Reduction for other advantages and disadvantages.

Having a statistically significant trend in the data due to climate change might be problematic for further use. The practitioner might aim for a baseline without any climate change trend or might need to remove the climate change trend prior to other data transformation methods. In these situations, the baseline can be adjusted (see **Section 3.3** – Adjustment).

6.2.3. Specific considerations for the extension of the baseline

Using the climatic baseline and doing an extension can be an interesting way to produce a future scenario. See **Section 3.4** – Extension for recommendations, advantages and disadvantages.

If the correction factor is computed from the baseline and can be attributed to climate change (**Appendix B** – Detection and attribution in the context of climate change), it is reasonable to extend the trend ~15 years. Indeed, at this time horizon, the emissions scenarios are similar. As mentioned in **Section 3.4** –Extension, a detection and attribution exercise is strongly recommended to determine whether the correction factor can be attributed to climate change (see **Appendix B** – Detection and attribution in the context of climate change).

See also the first consideration discussed in **Section 6.2.4** – Specific considerations for the delta method.

6.2.4. Specific considerations for the delta method

There are three considerations when opting for the delta method at this stage of the modeling chain.

One: as mentioned in **Section 3.5** – Delta method, the delta method will project past climate cycles and past climate trends into the future. This is a limitation of this method and it can become problematic for baselines demonstrating strong trends (e.g. temperature). **Figure 15** of **Section 3.5** (Delta method) demonstrates this concept: the projected baseline (black line) does not exhibit the same trend as the climatic simulation (red line). Part of this limitation can be overcome by adjusting the baseline prior to using the delta method.

Two: the delta method is typically applied to 30-year periods. This time period is typically chosen for three reasons: it covers most natural variability; it enables the calculation of most relevant statistics (as the minimum number of data for statistical analysis is met); and it reduces the risk of finding a significant trend in the data. In some situations, for the valuation of assets, a 30-year period is not long enough (e.g. computation of a NPV over 90 years). The practitioner can use longer future and reference periods if the information is available (see the example in **Section 6.5.1** – Applying a delta method to a hydrologic baseline). If the information is not available, the practitioner should adjust the approach and document its limitations.

Three: after the delta method, the practitioner could use the direct method in the rest of the modeling chain or use the delta method again at the hydrology-to-energy stage. In the latter case, it is recommended that the reference period of the climatic and hydrologic baselines be consistent or compared statistically.

6.2.5. Specific considerations for bias correction

There are many specific technical considerations to keep in mind when performing bias correction on raw climatic simulations. The first is the potential need for downscaling, prior to or during the bias-correction process. Other considerations include: GCM selection (see **Appendix C** – GCM selection methods); the need to adjust calendars into something workable by the hydrologic model (for GCMs not using a standard calendar); the proper processing of values outside the range of the historical distribution; preserving the climatic simulation trend; avoiding physical inconsistencies between variables of the same simulation (e.g. minimum and maximum temperatures); and performing bias correction at different time scales. These subjects are well documented in the literature (Agbazo and Grenier, 2019; Cannon et al., 2015; Haerter et al., 2011; Hempel et al., 2013; Maraun and Widmann, 2018).

Another important consideration at this stage is that even if the bias correction method offers several advantages, the bias-corrected and downscaled simulations still have limitations that need to be documented and considered in the rest of the modeling chain.

6.2.6. Next steps

a) Apply data transformation, if needed.
b) Assess the adequacy of the climatic scenarios (see **Appendix E** – Validation of climate products).
c) Run hydrologic simulations with climatic scenarios.
d) Proceed to **Section 6.3** – From hydrology to energy.

6.3. From hydrology to energy

This section explains how to integrate the hydrologic baseline and the climate change data related to hydrology (**Section 5.5** through **5.7**) in the energy model as shown in **Figure 20**. **Table 8** presents the most common and relevant data transformation methods for hydrologic simulations/results. **Section 6.3.1** outlines specific considerations at this stage of the modeling chain. **Section 6.3.2** addresses the reduction and the adjustment on the climatic baseline, while **Section 6.3.3** through **6.3.5** address respectively the extension, the delta and bias correction methods. The direct method is not presented, as its implementation presents no specific considerations. Also, note that advantages and disadvantages of each method are not repeated, as they appear in **Section 3**. **Section 6.3.6** presents the next steps.

Table 8 Use of data transformation methods with the baseline and climate change data for the integration of hydrologic data/results into an energy model.

	Direct	Reduction	Adjustment	Extension	Delta	Bias correction
Hydrologic baseline	●	●	●	●	●	
Simulation based on the climatic baseline	●			●	●	
Hydrologic simulations (from Section 5.5 or 6.2)	●			●	●*	●
Global datasets and proxies				●	●	
Pre-computed results from hydrologic data				●	●	

*At this stage, the delta method should be used if there are inconsistencies between the hydrologic model(s) used to integrate the climatic baseline (simulation based on the climatic baseline) and the hydrologic simulations.

6.3.1. Specific consideration: regulated vs. naturalized

The most important consideration at this stage is potential inconsistency between the hydrologic baseline and the hydrologic simulations (e.g. simulation based on climatic baseline, hydrologic simulations, global datasets and proxies, and most often pre-computed results from hydrologic data). The hydrologic baseline is tainted by errors and heterogeneities (see the Box Hydrologic drivers and limitations of the hydrologic baseline in **Section 4.2**) and is influenced by all regulated upstream reservoirs and hydraulic structures. In other words, it inherently records all water management decisions or regulation at upstream reservoirs and hydraulic structures. On the contrary, the simulations are often naturalized, meaning that they do not take into account water management decisions at reservoirs and hydraulic structures. **Figure 21** shows an example of the impact of water management decisions on a time series of streamflow. The magnitude of this issue depends on upstream reservoir storage capacity, and on the time step of interest in the assessment, among other factors. For example, upstream reservoirs with moderate storage may impact the monthly timing of flows, but average volume may be unaffected. Refer to **Section 7.7** – Model scaling and **Section 7.8** – Benefits of hydrologic and water management modelling.

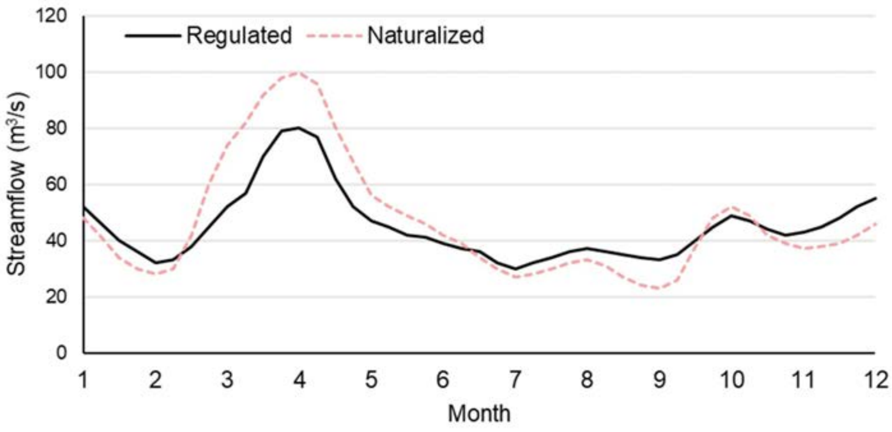


Figure 21 Example of the influence of water management decisions on a time series

6.3.2. Specific considerations for reduction and the adjustment of the baseline

The same considerations apply when using the reduction method on the hydrologic baseline; refer to **Section 6.2.2** – Specific considerations for reduction and the adjustment of the baseline.

As with the climatic baseline, the presence of a statistically significant trend in the hydrologic baseline may be problematic for further use in the modeling chain (e.g. projecting a land use change trend in the future with the delta method). The adjustment of a hydrologic baseline is somewhat more challenging than the same manipulation of the climatic baseline, because of the large number of hydrologic drivers.

- If the correction factor is computed from a simulation, integrating a single hydrologic driver (e.g. climate change) would remove the influence of this driver only (e.g. it would not remove the influence of land use changes).

6.3.3. Specific considerations for the extension of the baseline

Using the hydrologic baseline and doing an extension is an interesting option to produce a hydrologic projection. See **Section 3.4** – Extension for recommendations, advantages and disadvantages. However, it presents more challenges than manipulating the climatic baseline, as the number of drivers in the hydrologic baseline is higher.

- If the correction factor is computed from the baseline, even when a proper detection and attribution has been completed, there is a risk of extending the baseline according to a trend caused by multiple hydrologic drivers at the same time (e.g. climate changes and land use changes). Also, refer to **Section 6.2.3** – Specific considerations for the extension of the baseline for a time horizon limit.
- If the correction factor is computed from simulations integrating one hydrologic driver (e.g. climate change), the resulting hydrologic projection ignores the potential future influence of other drivers (e.g. land use changes).

See also the first consideration discussed in **Section 6.2.4** – Specific considerations for the delta method.

6.3.4. Specific considerations for the delta method

When applying the delta method at this stage of the modeling chain, the first and second considerations discussed in **Section 6.2.4** – Specific considerations for the delta method still apply.

The first of these considerations – projecting past climate cycles and past climate trends into the future – is exacerbated for the hydrologic baseline because of the large number of hydrologic drivers. Land use changes and changes in the regulation of upstream reservoirs and hydraulic structures through time are also projected in the future. See **Section 7.5** – Data transformation.

The issue of regulated baseline versus naturalized hydrologic simulations can also become challenging at this stage, as the regulation might impact monthly and annual volumes. See **Section 7.7** – Model scaling.

6.3.5. Specific considerations for bias correction

Unlike bias correction of climatic simulations, bias correction of hydrologic simulations is less understood and documented in the literature. Bias correction is used in short-term hydrologic forecasting (e.g. in ensemble streamflow prediction), but not often for long-term hydrologic simulations integrating climate change.

Specific considerations for bias correction of hydrologic simulations, reported in the few existing scientific papers, include: the need to properly process the values located outside the range of the historical distribution; and the need to respect both the mass balance at different locations in the watershed and across the seasons (Snover et al., 2003). The need to preserve the hydrologic simulation trend, such as for the climatic simulations, also applies (see **Section 6.2.5** – Specific considerations for bias correction).

Despite the lack of literature, the practitioner may still find themselves in a challenging position where they consider the bias correction of hydrologic simulations to be necessary. For example, this could be the case if the bias of a hydrologic simulation is slightly too large for the direct method, but the delta method would result in a loss of important information (such as changes in sequences). In these situations, the methods described in **Section 3.6** – Bias correction are applicable, but the practitioner might want to pay special attention to the considerations described in the previous paragraph.

6.3.6. Next steps

a) Assess the adequacy of the hydrologic simulations (see **Appendix G** – Validation of hydrologic simulations).

b) Apply data transformation, if needed.

c) Assess the adequacy of the hydrologic scenarios, except for hydrologic simulations and pre-computed results from hydrologic baseline. See **Appendix G** – Validation of hydrologic simulations.

d) Run energy simulations with hydrologic scenarios.

e) Proceed to **Section 6.4** – From energy to value.

6.4. From energy to value

At this stage, the practitioner should have an energy simulation based on the baseline, as well as energy simulations integrating climate change.

The direct method is typically the most relevant one at this stage of the modeling chain. Indeed, even though other data transformation methods from **Section 3** may be numerically applicable, applying them is generally not recommended anymore, because this would bypass the watershed's physical reality and constraints, such as storage and turbine capacity. Such a bypass would blindly modify the timing and amount of energy produced and would directly impact asset valuation.

Nonetheless, the energy simulations integrating climate change may have a bias when compared to the energy simulations based on the baseline. As discussed in **Section 7**, this can be problematic, as organizations are often interested in comparing simulations integrating climate change with the simulations based on the baseline.

If the practitioner still needs to perform data transformation techniques at this stage of the modeling chain, the next section presents general considerations.

6.4.1. General considerations

The practitioner should keep in mind that historical energy values contain information about outages, maintenance and dam regulation. Some energy models may represent outages and maintenance with an outage factor, and will represent the regulation of the dam with a series of automated regulation rules.

As such, practitioners planning to use the extension or the delta method with historical energy values will project past outages, maintenance and regulation into the future.

6.4.2. Next steps

a) Assess the adequacy of the energy simulations.

b) Apply data transformation, if needed.

c) Assess the adequacy of the energy scenarios.

d) Run value simulations with energy scenarios.

6.5. Examples

6.5.1. Applying the delta method to a hydrologic baseline

Figure 22 presents an example of the delta method applied to a hydrologic baseline in the modeling chain. The delta used in this example can come from multiple sources, and the climatic baseline is only used during the hydrologic model calibration.

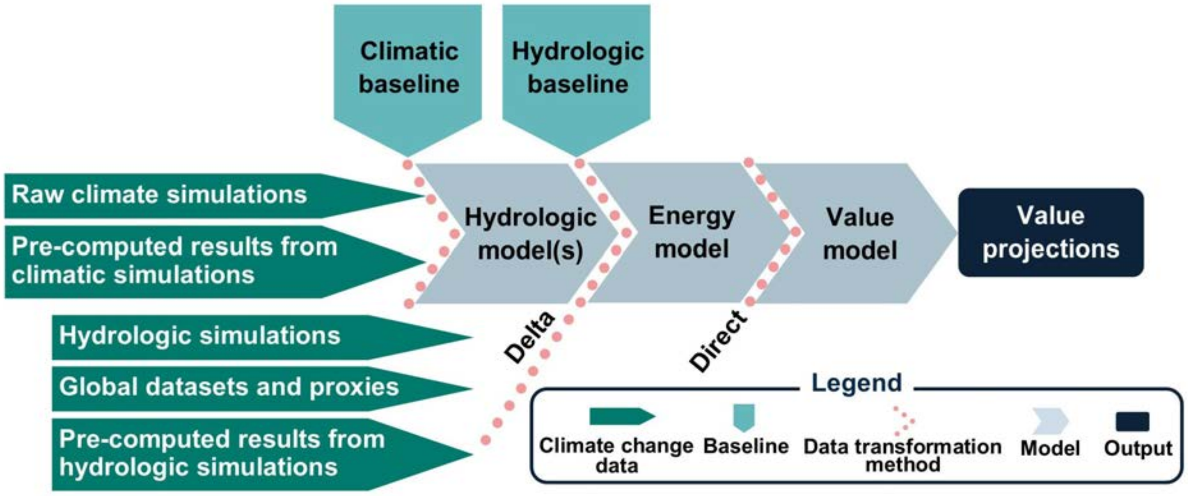


Figure 22 Example of the modeling chain when the delta method is applied to the hydrologic baseline. The delta can be computed with different types of climate change data. The direct method is used in the rest of the modeling chain. In this example, the climatic baseline is only used during the hydrologic model calibration.

Panel A of Figure 23 shows the hydrologic baseline (in black) and the hydrologic scenarios (in gray) obtained by applying the delta method to 10 hydrologic simulations (RCP 4.5). The deltas for each hydrologic simulation are computed between the future (2016–2070) and reference (1961–2015) periods, at the annual scale. The delta is applied to the hydrologic baseline to obtain 10 hydrologic scenarios. In this example, it is possible to compute the delta for periods of 55 years, as it is drawn from the continuous hydrologic simulations presented in Figure 24. This type of information might not always be available. For example, working from the information referenced in Table 6 (Section 5.7 – Pre-computed results from hydrologic simulations), the practitioner would have data only for specified 30-year periods: 1961–1990, 2010–2039, 2040–2069 and 2070–2099. Also, note that the use of only one RCP is not a reasonable practice, as stated in Appendix I – Best and good practices for the ensemble approach. It is used in this example for the sake of clarity and to limit the number of figures in the Guidebook.

Panel B of **Figure 23** shows the energy simulations based on the hydrologic baseline and on the hydrologic scenarios (simulations based on CC), and panel C shows the revenues. Note that the direct method is used between the energy and value stages.

The comparison between the traditional method and the method with climate change is presented in **Figure 25** for revenues and **Figure 26** for the NPV. As the delta method is used at the hydrologic stage and the direct method is used afterward, this comparison is possible (see **Section 7.6** – Consistency in comparison). Note that the same hypotheses were made for the simulation based on the baseline and the simulation based on the traditional method (electricity prices, cost of operation, etc.).

When compared to the traditional method, simulations integrating climate change present a favourable result on both revenues (**Figure 25**) and NPV (**Figure 26**). The uncertainty visible on both graphs by the dispersion of the simulations integrating climate change is due to natural variability (implicitly represented using different initial conditions for each climate model) and to the different climate model responses when using the same emissions scenario.

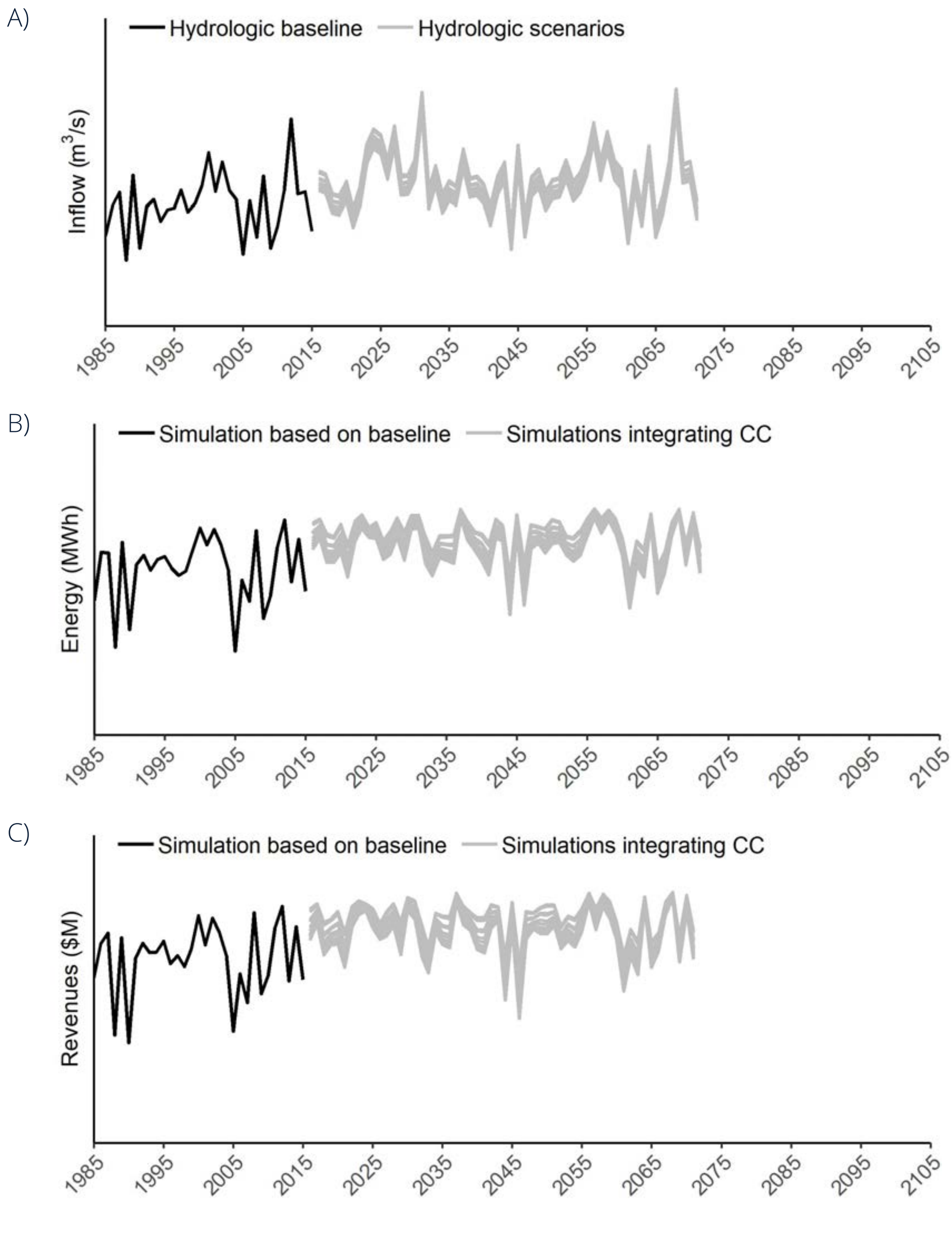


Figure 23 Example of results obtained when the delta method is applied to the hydrologic baseline. Panel A) shows inflows, B) energy and C) revenues. The delta method was applied to the hydrologic baseline (black). The delta was computed from 10 hydrologic simulations to produce hydrologic scenarios (to produce 10 gray lines). The direct method is used in the rest of the modeling chain to produce simulations based on baseline (black) and simulations integrating climate change.

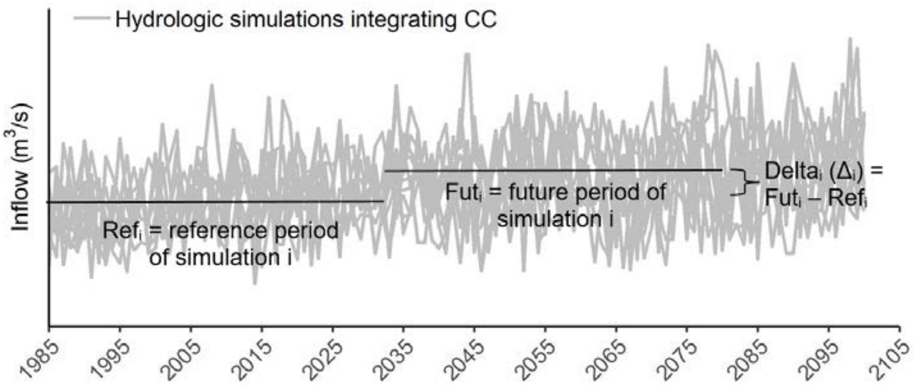


Figure 24 Example of continuous hydrologic simulations (gray) on which a delta can be computed. The hydrologic simulations were produced using a hydrologic model and climatic simulations from one RCP and 10 climate models. The delta was computed between the future and reference period of the hydrologic simulation (to produce 10 deltas).

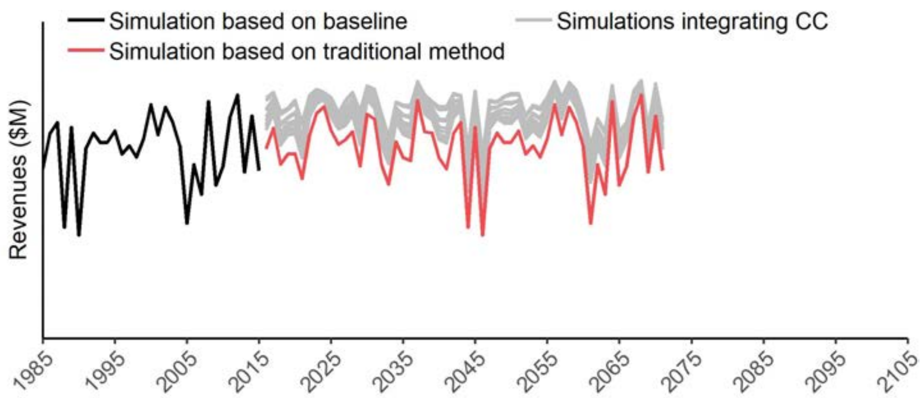


Figure 25 Comparison of simulated revenues based on the baseline (black), on the traditional method (pink) and on simulations integrating climate change when the delta method is applied to the hydrologic baseline (gray).

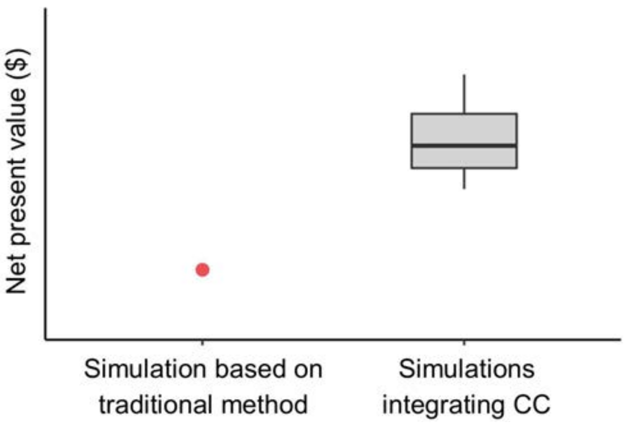


Figure 26 Comparison of the NPV based on a simulation using the traditional method and simulations integrating climate change.

6.5.2. Bias correction of climatic simulations and direct method with the hydrologic and climatic baseline

The example presented in Figure 27 features three types of inputs: climatic and hydrologic baselines, as well as raw climatic simulations. First, the hydrologic model is calibrated with the climatic and hydrologic baseline. Raw climatic simulations are then downscaled and bias-corrected with the climatic baseline. The climatic and hydrologic baselines, as well as post-processed climatic simulations, are fed into the modeling chain to obtain the results presented in Figure 28.

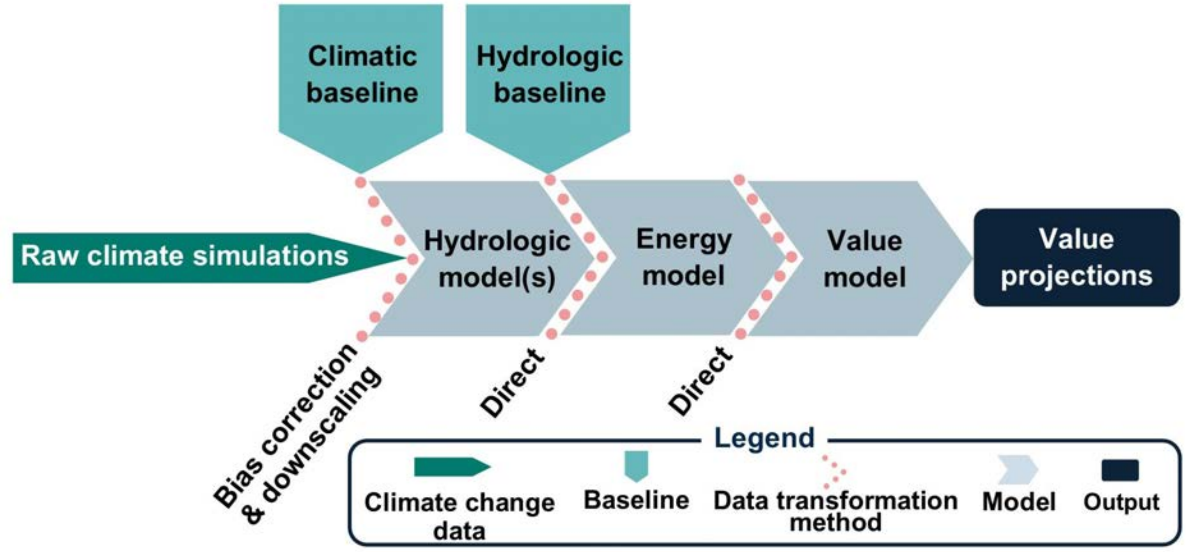


Figure 27 Example of the modeling chain using as inputs the climatic and hydrologic baselines, as well as raw climatic simulations. Bias correction and downscaling are applied to the raw climatic simulations prior to their integration into the modeling chain.

Panel A of Figure 28 shows the climatic baseline in green, the hydrologic baseline in black and the hydrologic simulations fed by 10 downscaled and bias-corrected GCMs simulations for RCP4.5 in gray. Panel B and C show, respectively, the energy and the revenues when the direct method is used at these stages. Note that the use of only one RCP is not a good practice, as stated in Appendix I – Best and good practices for the ensemble approach. It is used in this example for the sake of clarity and to limit the number of figures in the Guidebook. Figure 29 compares the annual average inflows, energy and revenues for the reference period (1984–2015) and for the future period (2016–2045) for simulations based on hydrologic baseline, simulations based on climatic baseline and simulations integrating climate change.

Figure 28 and Figure 29 illustrate some of the challenges the practitioner will face with the modeling chain. First, the simulation based on the climatic baseline (reconstructed hydrology) appears to be biased, when compared to the hydrologic baseline. This bias can have several causes, such as the calibration of the hydrologic model or the time period used for the calibration. There is also a similar issue between the simulation based on the climatic baseline and the simulations integrating climate change, when compared in the reference period (1984–2015). This bias can also have several causes, such as the post-processing of climate data or the time period used for the post-processing. These biases are transmitted to the rest of the modeling chain, as the direct method is used, and the values for energy and revenues produced by the simulations integrating climate change are therefore lower than with the baselines. Because of these biases, the practitioner cannot compare directly the simulations based on the hydrologic and climatic baseline with the simulations for the future period integrating climate change. Doing so would obscure the real climate change signal. The practitioner could compare the future and reference periods of the simulations integrating climate change or apply another data transformation method (delta or bias correction).

Indeed, even if the absolute values are lower because of biases, the conclusion of that specific example should be that climate change increases inflow, energy and revenues when simulations integrating climate change for the reference period (1984–2015) and future period (2016–2045) are compared (Figure 29). The uncertainty suggested by the dispersion of the boxplots of simulations integrating climate change is due to natural variability (implicitly represented using different initial conditions for each climate model) and to the responses of the climate models to the same emissions scenario.

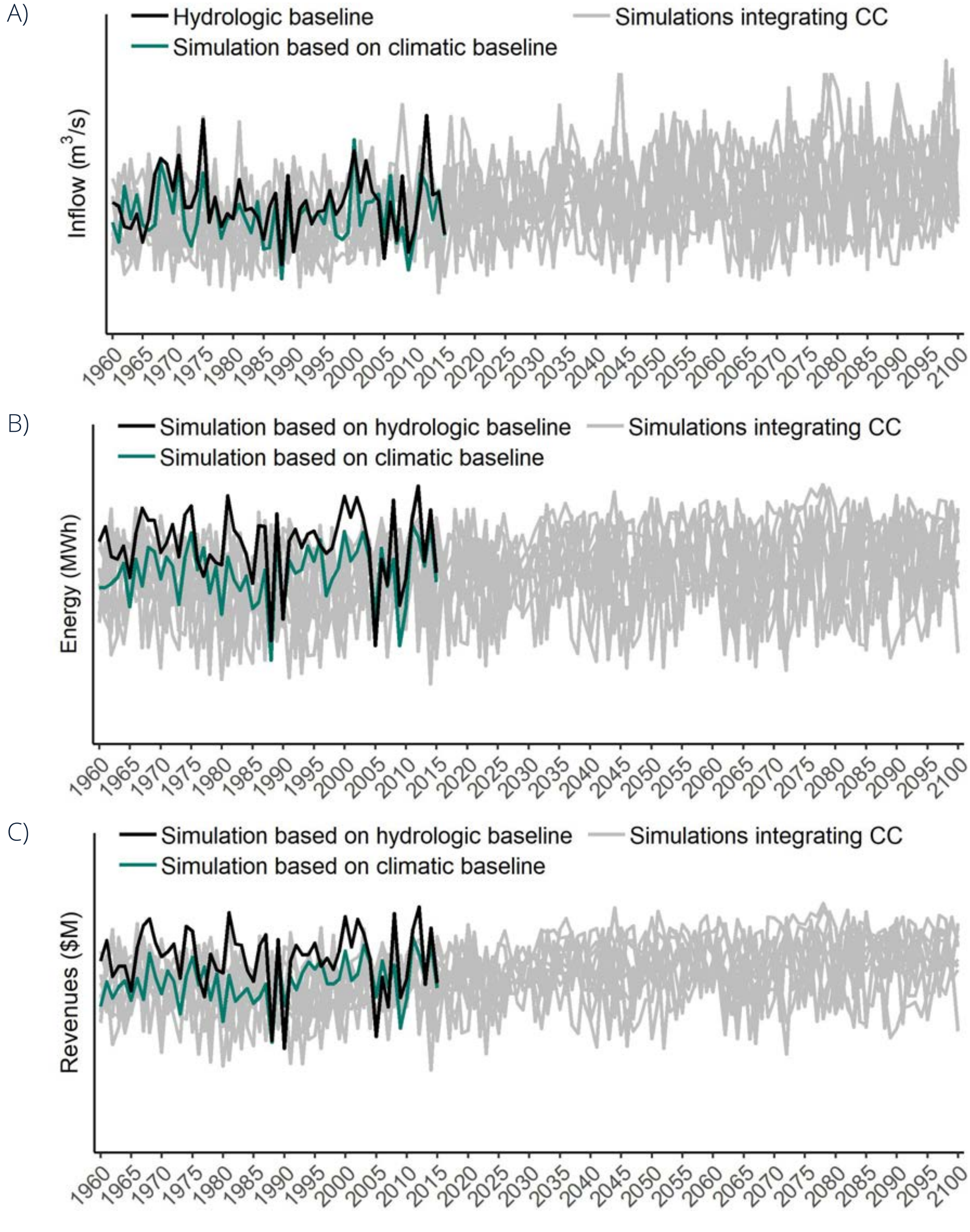


Figure 28 Example of results obtained from the bias correction of climatic simulations and the use of the direct method on the hydrologic and climatic baselines. Panel A) shows inflows, B) energy and C) revenues. The climatic baseline (green), the hydrologic baseline (black) and post-processed climatic simulations (gray) are fed into the modeling chain. The direct method is used between the hydrology, energy and values stages. The results are presented for one RCP and 10 climate models (10 simulations).

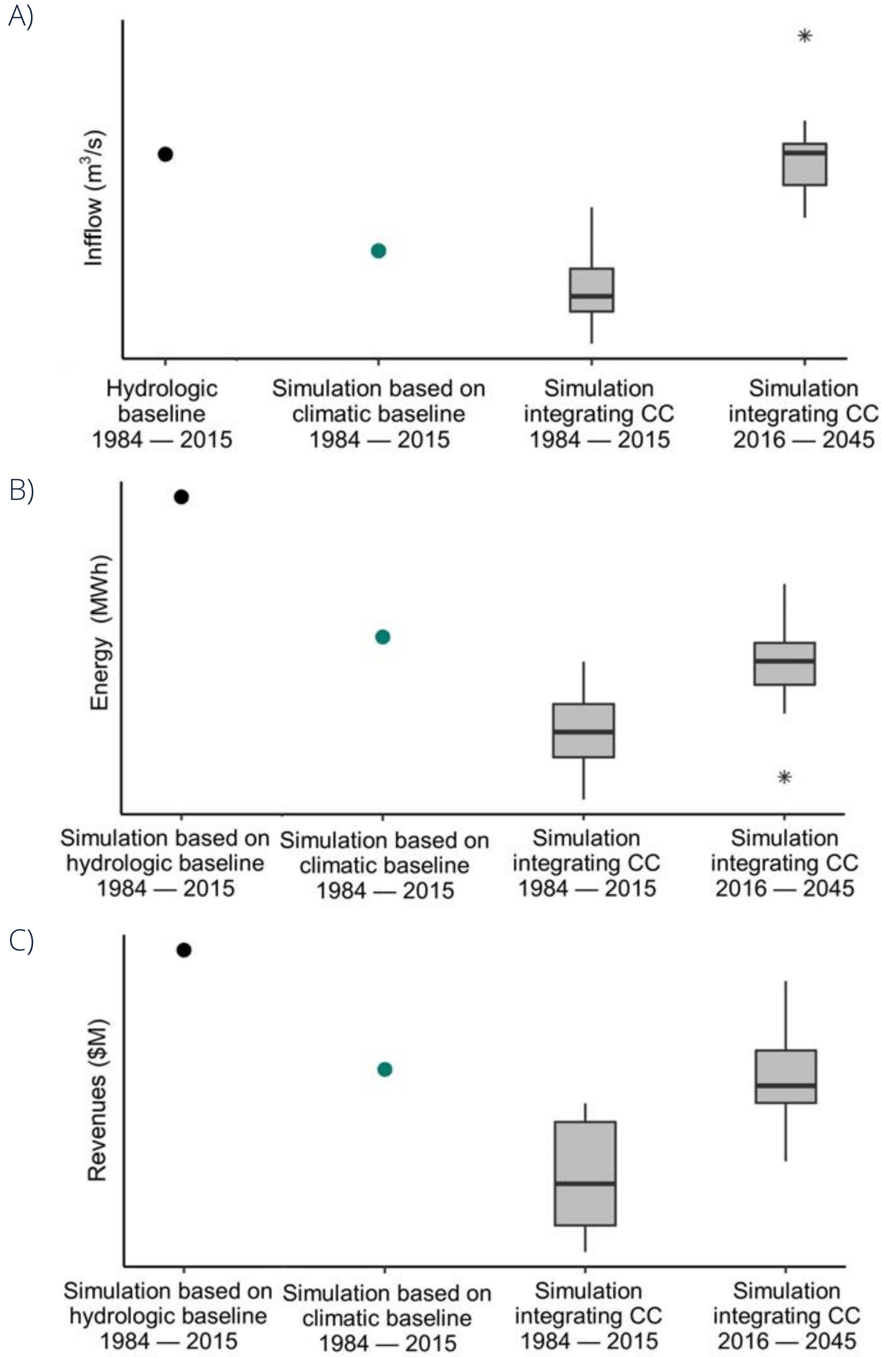
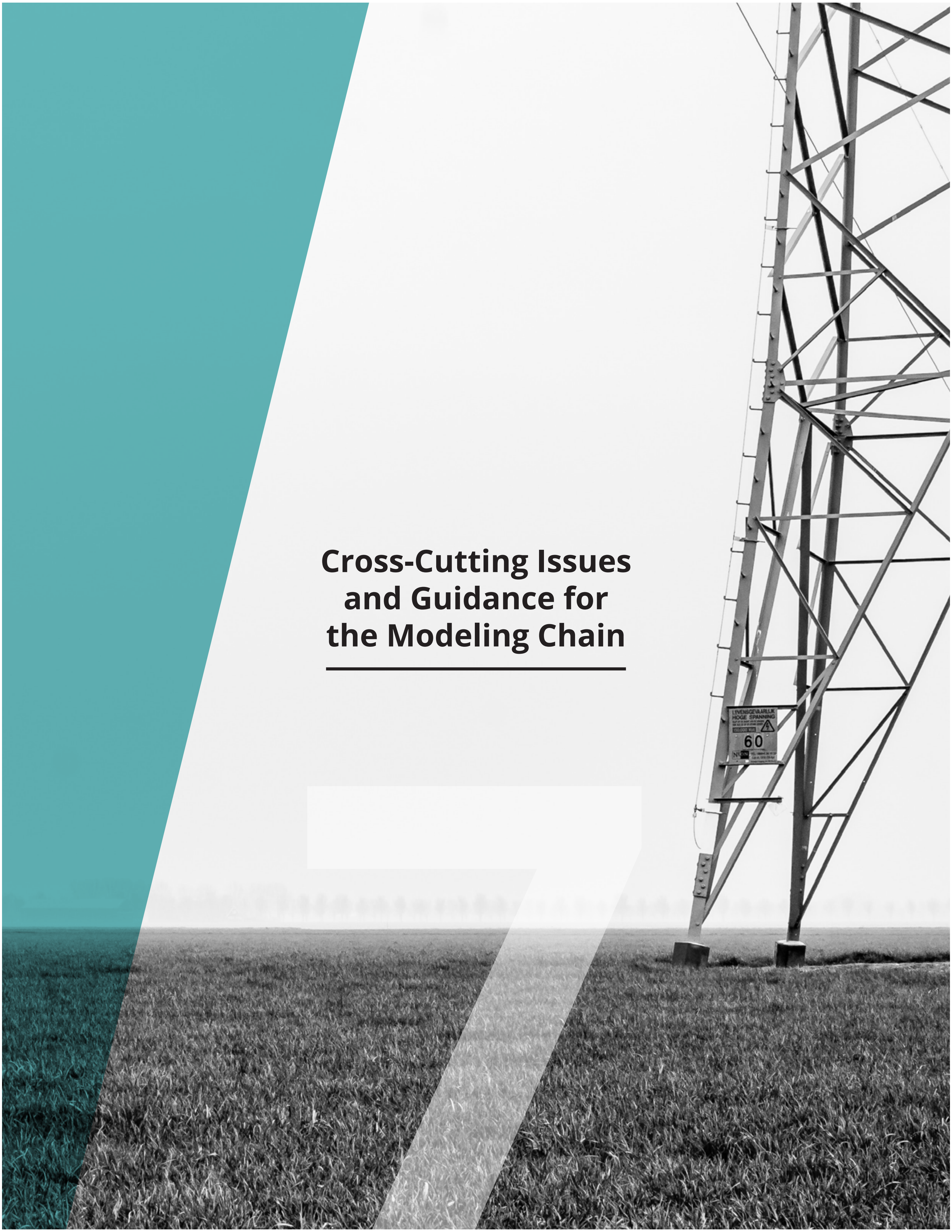


Figure 29 Comparison of the average A) inflows, B) energy and C) revenues for simulations based on the hydrologic (black) and climatic (green) baselines, as well as for simulations integrating climate change (reference period: 1984–2015 and future period: 2016–2045). Outlier values are marked with a star.

7

Cross-Cutting Issues and Guidance for the Modeling Chain



This section looks at the cross-cutting (applying at several steps) issues when integrating climate data into the valuation of hydropower assets. This section will consider the consistency of information used throughout the assessment, concepts for pre-planning and the careful selection of the options presented in Section 3 through 6. While pre-planning does not eliminate all technical challenges and surprises, it can help avoid pitfalls and inconsistencies.

Section 7 also provides guidance on how to integrate all of the elements of the modeling chains shown in Figure 20 of Section 6.1. However, many considerations related to integration and coherency remain subject to the needs and expertise of the practitioner. This is particularly true, as an accepted standard of practice for climate change integration has yet to emerge from the literature, regulations or in practice.

Section 7.1 describes organizational considerations for the integration of climate change; Section 7.2 and 7.3 outline considerations when averaging, selecting and presenting results. Section 7.4 focuses on data used within the modeling chain and how to ensure coherence of the full assessment. Section 7.5 considers data transformation. Section 7.6 focuses on the importance of making consistent comparisons between historic baselines and future projections. The final sections discuss considerations specific to the model's spatial and temporal scales (Section 7.7) and the benefits of hydrologic and water management modeling (Section 7.8).

7.1. Managing the change in organizational practices

When using climate data for the first time, practitioners must anticipate organizational hurdles. Good planning is essential.

Indeed, as stated in Section 2 – Methods for income-based valuation and uncertainties, the industry's traditional practice is to use the hydrologic baseline. There is generally a strong belief in the ability of the hydrologic baseline (observed data) to adequately represent future conditions, despite the shortcomings (identified in Section 4.2 – Hydrologic baseline). Starting to think in terms of a climatic baseline is an important step for organizations. It is important to acknowledge that both the climatic baseline and hydrologic baseline have recognized merits and shortcomings, which should factor into the valuation process.

Also, since the industry lacks a generally accepted best practice, the practitioner should understand and communicate early on the options described in Section 3 through 6, and seek expert advice when needed.

7.2. Considerations for selecting and averaging simulations

The modeling chain requires practitioners to deal with several challenges and constraints (computational time, human resources, complexity and size of the dataset, etc.). It is not always possible to use and/or analyze all data; compromises have to be made between analyzing all possible data, making informed selections and/or using averages. Climate change complicates this situation further, as it implies working with the ensemble approach (larger datasets) and a non-stationary climate.

Some sort of selection of data might be necessary prior to their introduction into the modeling chain. While there is no universal way to meet this challenge, here are a few guidelines for various stages of the assessment.

- Simulations should be averaged only during the last step of the modeling chain and only for presentation purposes. This also applies to averaging simulations from a same emissions scenario (e.g. for several GCMs) or a same GCMs (e.g. for several members/realization of a same GCM). Averaging simulations flattens interesting characteristics of the time series and implies a large degree of information loss.
- When dataset complexity and size become a challenge, prioritize informed selection of few representative simulations over averaging simulations before their integration into the modeling chain.
- The variability of the results should always be considered, be it for the selection of simulations or for the assessment itself. This can be accomplished by analyzing the 5th, 50th and 95th percentiles of the ensemble. It is generally recommended to exclude the most extreme scenarios, unless required for the assessment

7.3. Considerations for presentation of results

When communicating results of their study, the practitioner might have to use simple descriptions or plots that also convey the full range obtained.

- The practitioner could:
  - Present the entire range of results of the ensemble approach and explain the range (several emissions scenarios, GCMs, realization, etc.).
  - Present the range of results by emissions scenarios, GCMs, etc.

- Models may be averaged for presentation purposes; however, the variability of the results should also be presented (e.g. 5th, 50th and 95th percentiles of the ensemble). The practitioner may also consider using suitable vocabulary. The IPCC 2007 report uses a vocabulary well suited to communicating the results of climate changes studies (IPCC, 2007).
- Consider displaying percentiles of specific indices of interest (such as change in annual streamflow).
- Consider whether to use absolute numbers (e.g. generation will increase by 1 GWh/yr) or relative numbers (e.g. generation will increase by 5%).
- When comparing two periods of time (e.g. reference and future periods in a boxplot graph):
  - Use the same time period (e.g. 30 years).
  - To minimize the impact of fluctuations due to natural variability, consider using a time period of at least 30 years.
- Presenting select individual simulations may convey interesting information.

7.4. Consistency of climatic data and time periods

To avoid introducing inconsistencies and biases in the valuation, consistency of climatic data throughout the modeling chain is essential. As stated in **Section 6.2.1** – Specific consideration: Dataset coherence, the practitioner should not interchange precipitation and temperature from different products or simulations because they are part of a consistent physical system. For this reason, each product or simulation should be treated independently.

Consistency of the climatic baseline is also important. The climatic baseline is used several times during the valuation assessment: to calibrate and validate of the hydrologic model, to post-process climate data and to make simulations (reconstructed hydrology). For discussion purposes, this Guidebook focuses on precipitation, as it is a major driver of hydrology and therefore of hydropower production. As shown in the Box Variation in Precipitation Data, different precipitation products have characteristics unique to their development. The same concepts apply to temperature.

VARIATION IN PRECIPITATION DATA

Precipitation products typically have characteristics unique to their development. **Figure 30** shows accumulated precipitation data at a single location for the period 2007–2012, derived from different products. The brown line shows the observations from a nearby meteorological station. The green line is from the Canadian Daily Gridded Precipitation product (Hutchinson et al., 2009), which is a gridded dataset that spatially interpolates weather station data and accounts for undercatch. The black line is from the Canadian Precipitation Analysis (CaPA – Mahfouf, Brasnett and Gagnon, 2007), which uses an optimal interpolation algorithm to merge meteorological station observations and radar on a background short-range weather-forecast product. While all three are derived from the same core precipitation station data, differences in their methodologies and algorithms result in nominally different characteristics, which can influence the model simulation. For example, the CaPA product clearly shows greater winter precipitation, which at this particular site indicates a greater snowpack. These products also represent intense precipitation events, such as convective storms, differently (not shown). A storm may miss or directly hit a gauge, causing a large differences relative to the areal averaged gridded products. A similar phenomenon can occur with the ANUSLIN interpolation between gauges of Hutchinson et al., (2009), whereas the CaPA product may detect a storm from the NWP output. These discrepancies can worsen when gauge density is low.

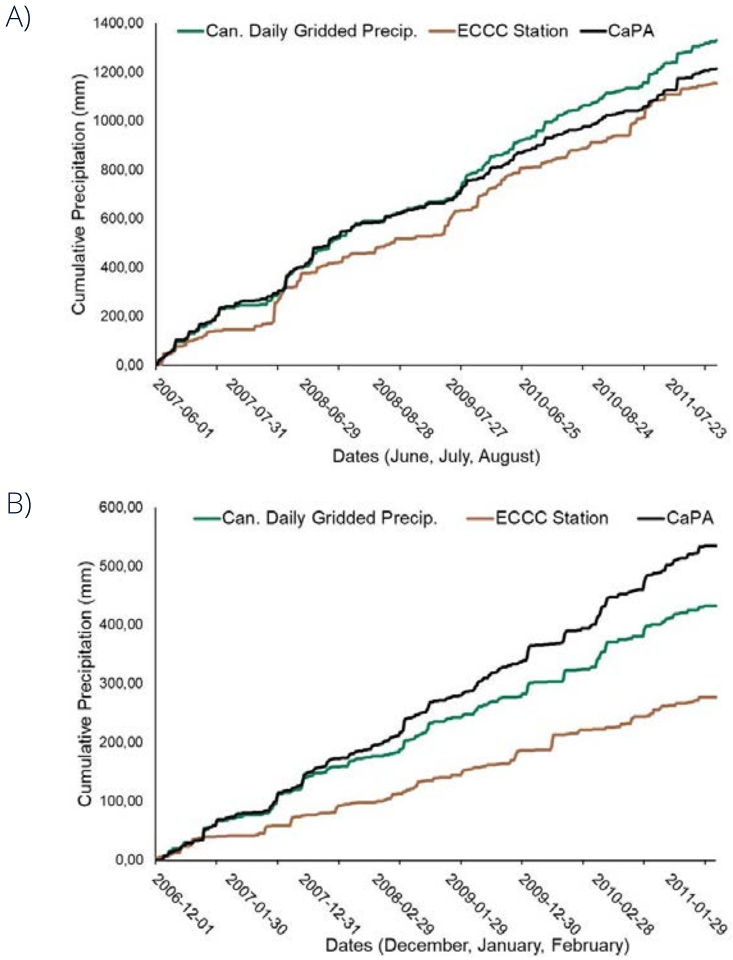


Figure 30 Accumulated precipitation for three climate products during summer (panel A) and winter (panel B).

Systematic biases could be introduced, particularly in hydrologic simulations, if the climatic baseline is inconsistent throughout the modeling chain. Each of the three products in **Figure 30** could have been chosen to calibrate a hydrologic model. With a single hydrologic baseline, the model parameters would compensate for the different precipitation data during calibration to simulate the same hydrologic time series. The hydrologic simulation could vary considerably if the parameter differences were significant enough and the practitioner interchanged the precipitation products. For this reason and whenever possible, the same precipitation product should be used throughout the modeling chain (model calibration, post-processing of climatic simulations and reconstruction of hydrology). For example, if the Canadian Gridded Daily Precipitation (Hutchinson et al., 2009) dataset is used to post-process climatic simulations, it should also be used for model calibration and to simulate the reconstructed hydrology. Otherwise, this could result in an inconsistency between the reconstructed hydrology and hydrologic simulations integrating climate change (based on climatic scenarios), when compared on the same period (see **Section 7.6** – Consistency in comparison).

The selection of a representative period of time (e.g. dry, wet, moderate periods) can also influence the model characteristics by influencing the parameters during the calibration process (KlemeŠ, 1986; Merz et al., 2011). For example, if the hydrologic model is calibrated using a short, hot and dry period and the climatic simulations are post-processed using a short, cold and wet period, it will introduce inconsistency in the modeling chain: the hydrologic simulations integrating climate change (based on climatic scenarios) might show a wet bias. Because of the potential sensitivity of the model results to precipitation, it is best to ensure the selection of a time period long enough to cover most natural variability and that is consistent throughout the modeling chain (climatic scenarios, calibration of hydrologic model, reconstruction of hydrology).

If consistency cannot be ensured across the time period or the climatic baseline, the delta method may be better suited to asset valuation. An alternative is to test the sensitivity of energy production to multiple climate baselines and check for consistent outcomes.

7.5. Data transformation

As stated in Section 2, the output from the climate model, hydrologic model and energy model would ideally be an accurate simulation of real-world physics. In practice, a model is an abstraction of reality, or a plausible reality, where some form of transformation/manipulation of the data is required to most accurately reflect actual outcomes.

Section 7.5.1 provides guidance on where in the modeling chain to apply data transformations; Section 7.5.2 outlines considerations when trends are present in the baseline dataset; and Section 7.5.3 considers the potential error of over-fitting statistical functions to transform data.

7.5.1. Which one to apply and where?

At each stage of the modeling chain, the practitioner needs to decide which transformation method to use (direct, extension, delta method or bias correction) before integrating data into the next step of the modeling chain. The adequacy of the simulation before data transformation, compared to the baseline, can provide the practitioner with hints on which method to select.

The direct method is best reserved for simulations that have relatively small biases for every index of interest, using criteria described in Appendix G.3.2 – Validating the hydrologic simulations. This represents a near-ideal scenario for the practitioner. The delta method is recommended when the performance of the simulation is acceptable according to Appendix G – Validation of hydrologic simulations, but biases remain (between the simulations and baseline) that cannot be justifiably modeled or corrected. This may include difficulties such as unexplainable trends in the baseline or a hydrologic influence that cannot be justifiably extended into future-period simulations. Bias correction is recommended when the inconsistencies in the simulation data, compared to the baseline, can be statistically well described and the correction applied reliably to the future period (see specific considerations for bias correction in Section 6.2.5 and 6.3.5). In considering these options, the practitioner should recognize that scientific and engineering literature documents multiple bias-correction and delta methods, and that each one has particular strengths and weaknesses (Chen et al., 2013a; Maraun and Widmann, 2018). Refer to Appendix E – Validation of climate products to assess strengths and weaknesses of climatic simulations.

The practitioner must also consider which type(s) transformation to apply. For example, is a simple transformation for a difference in the mean appropriate, or should the method be applied across different quantiles (see Section 3.5 – Delta method and Section 3.6 – Bias correction)? It may also be pragmatic to apply the transformation on a seasonal or monthly basis, if warranted by the data. For the purpose of asset valuation for a single run-of-the-river station, it may not be as essential to accurately represent flow peaks, since these will be beyond the station's turbine capacity. It would certainly be more important for a dam-safety study, unless this unduly impacts construction costs. **Appendix H** – Sensitivity Analysis can be used to assess the sensitivity of the final results. These considerations are prudently balanced against the needs of the organization in terms of scope and resource availability.

The practitioner must also choose at which stage(s) of the modeling chain to apply a selected transformation method. In general, it is best to apply the method as early in the modeling chain and as close to the source as possible, to preserve mass and energy balances. If using the climatic baseline, the transformation method must be applied to precipitation and temperature data before they are integrated into the hydrologic model. To preserve the water balance, precipitation entering the model must be equal to the change in storage and discharge from the model. A subsequent manipulation of flow (e.g. applying a post-correction) could violate the water balance by artificially adding or removing water from the system. This will inherently impact the energy simulations. This water balance should be respected spatially within the watershed and also across time and seasons (Snover, Hamlet and Lettenmaier, 2003). For example, if the hydrologic simulation appears biased when compared to the baseline, it might be advisable to apply bias correction or the delta method. Known deficiencies should also be corrected, for example with the inclusion of a water management model to account for changing regulation regimes.

7.5.2. Trends

Trends in the baseline can quickly become challenging when conducting data transformations. As mentioned previously, identifying the cause and dealing with the trend are highly recommended (see **Appendix B** – Detection and attribution in the context of climate change) prior to proceeding with the next step. Failing to deal properly with a trend may result in unrealistic or implausible simulations.

For trends in historic data that are known to have a non-climatic origin, it is advisable to preserve or include them in a model to promote consistency, although no consensus exists on this topic. If a watershed has experienced major changes in land use over the years, for example, it is advisable to select a hydrologic model that can take those changes into account and replicate the associated trends. (see **Appendix F** – Selection and calibration of a hydrologic model).

The presence of a trend in the data can influence the bias correction, delta and extension methods, as seen in **Figure 31**. In this example, both data series are identical, although a strong trend was added for illustration. It is clear that the trended series has a wider range of variability (dashed lines) and standard deviation. If this variability were used carelessly in the bias correction, delta or extension method, the day-to-day variability would become greatly exaggerated and not represent realistic conditions. Removing trends (see **Section 3.3** – Adjustment), cycles and breakpoints (abrupt changes) from the dataset could be an important step to enable the transformation to represent realistic day-to-day weather patterns in the climatic or hydrologic data. The application of the trend from a climate dataset or re-application of observed trend should be carefully thought out by the practitioner and is best informed by a thorough understanding of its cause.

For future climate change simulations, the uncertainty will likely be dominated by the emissions scenarios and GCMs as lead time increases (see **Section 2.3** – Sources of uncertainty). For this reason, it is not recommended to continue trends or cycles into the long-term future without sound justification or full understanding of their physical causes. A practitioner should be able to review a simulation and determine if it is plausible for the watershed and generating station.

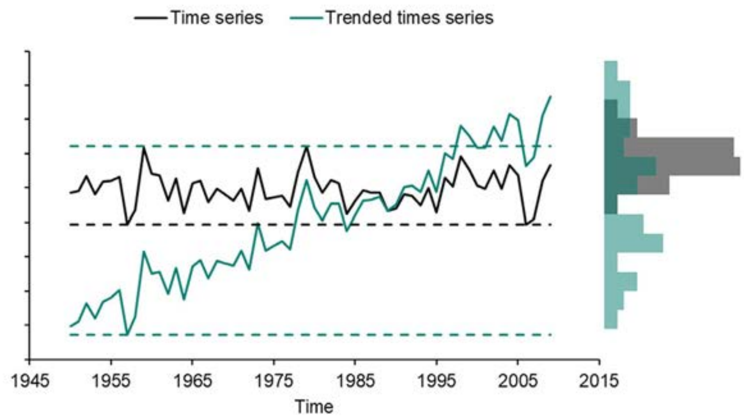


Figure 31 An illustration of the impact of a trend in a synthetic dataset on the statistical variability (min./max. in this case) of the data. The green time series is identical to the black time series, but with a strong trend added. Histograms to the right show the greater variability of the time series when a strong trend is added (green).

7.5.3. Over-fitting

Care must be taken to avoid over-fitting the data. This can be a problem in the extension method and during the trend-preservation step of bias-correction methods (see specific considerations for bias correction in **Section 6.2.5** and **6.3.5**). The problem can also arise during model calibration if the period used is too short.

Figure 32 shows an example of over-fitting, which occurs when the correction or function is fit too closely to limited data and loses its generalization ability, which invalidates its use for future conditions. In **Figure 32**, the high order polynomial fits the dataset (in blue) perfectly. However, new data added in the existing range (in green) have a much worse fit than if a linear function would have been used. Also, some functions, such as polynomials, splines and exponential functions are well known to risk over-exaggerating at the edges of the dataset. For example, continuing the curved function in **Figure 32** to an x-axis value of less than 1 or greater than 11 (where there is data) would result in y-values well beyond the observed range of the values in question. This phenomenon is not necessarily the result of over-fitting, but remains an important consideration when applying a statistical function beyond the limits of observed data.

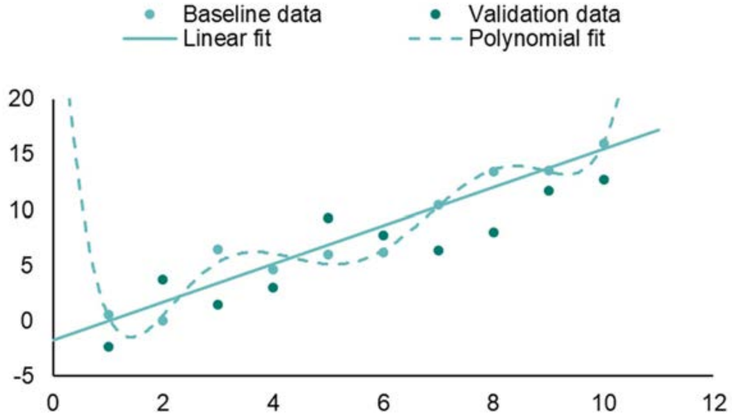


Figure 32 Over-fitting example. The function represented by the dashed line (polynomial) perfectly fits the baseline data (blue) but is not as generalizable as the linear fit of the data. This can be seen when validation data (green) is considered.

7.6. Consistency in comparison

Mathematician George Box famously said, "all models are wrong, but some are useful." It is highly unlikely that a model will produce a perfect simulation. To be able to discern reasonable difference from an error that needs to be rectified, the practitioner should have good prior knowledge of the system and establish reasonable targets and thresholds for variations from these targets. The practitioner may also do a sensitivity analysis to determine if the results obtained produce a meaningful difference in the outcome of the modeling chain (i.e. the asset value). If the results produce a meaningful difference, the decisions or models that lead to the outcome should be re-evaluated.

Consistency is important when doing comparisons within the assessment. The climatic and hydrologic baselines serve as the starting point for comparison. Hydrology and energy production may change due to many factors besides climate change, such as shifts in regulatory regimes, water management practices, market conditions or land use. As discussed in **Section 4.2** –Hydrologic baseline, this can make the hydrologic baseline more difficult to use and even complicate model calibration. However, the consistent application within a model of an element such as a new regulatory regime could produce a more accurate comparison. Regardless of the baseline chosen, the practitioner should be able to identify and explain differences with historic conditions. Consistency concerns may also impact the selection of climate change data (**Section 5**) and the integration of that information into the modeling chain (**Section 6**).

When the purpose of an evaluation is to inform decisions about an upgrade or major overhaul of a generating station, a key question often asked is: How will future conditions differ from baseline conditions? The natural inclination of most organizations is to compare the future scenarios obtained from the modeling chain to the results obtained using the traditional method. This is reasonable, as the traditional method is likely engrained in organizational processes and planning assumptions, and enables ready comparisons with existing studies. The results obtained using the traditional method may not be ideal, however, for a direct comparison with a future scenario (e.g. inconsistencies in the modeling chain leading to biases in the simulations). Practitioners should pay special attention to help ensure that future scenarios are properly integrated. In a real application, the modeling chain may yield implausible results for energy produced or asset value. A diagram such as **Figure 30**, which shows accumulated precipitation for different climatic products during summer, can help identify differences that may be noticeable only over long periods of time.

When results are implausible, the most robust solution would be to identify the source of the discrepancy and correct the issue(s) in the models. Otherwise, the practitioner must choose between further transformation or using the delta method to produce the final results (e.g. energy production or asset value) of the modelling chain. Before applying further transformations, the practitioner should seek to understand if the differences significantly affect the asset's determined value compared to other, external costs. For example, the potential costs of geotechnical or structural modifications may greatly exceed differences in energy production due to minor errors in the modelling chain.

An important source of discrepancy for the practitioner to consider is selection of the appropriate baseline period. The accepted recommendation for a period of climatologically relevant record is at least 30 years. During this time, however, the watershed may have experienced physical changes (potentially due to climate change), or regulatory changes that impact the flow available for hydropower production. Major outages or asset changes might also have impacted historic energy production or efficiency factors used for future simulations. The practitioner must ask: "How representative is the baseline?" Ideally, the baseline will consider a long period, but a practitioner may need to consider and justify a shorter period or multiple periods for the assessment.

7.7. Model scaling

The impact of simplifying assumptions in the modeling chain can depend greatly on the spatial and temporal scale of the models being considered. The IHA (2019) recommends a tiered approach to modeling efforts, increasing the level of detail as warranted. For example, models running at a monthly timestep may be sufficient on large stable systems that have little day-to-day fluctuation. This could simplify the sources and integration of climate data, favouring simpler techniques. In contrast, a model chain for a highly managed peaking river or cascade of stations may require models operating at a fine time resolution and spatial scale. The suitable integration of climate data into this model chain is more likely to require a water management model and greater care with climate data selection, transformations and overall integration. The interacting factors are likely to produce a more sensitive outcome at the end of the modeling chain. This can also be true when using a nested modeling approach where a coarse resolution model is used to feed a higher resolution model for specific parts of a watershed or timescales of interest.

7.8. Benefits of hydrologic and water management modeling

As noted in the previous sections, the integration of climate change in the modeling chain might necessitate the implementation of a hydrologic model. There are several distinct advantages to the inclusion of hydrologic modeling that an organization should consider. However, these advantages become manifest only with proper calibration and understanding of the model (see **Appendix F** – Selection and calibration of a hydrologic model). It is worth noting that most of these benefits accrue when the model is either developed by or for an organization specifically. Access to externally developed hydrologic simulations (**Section 5.6** – Global datasets and proxies) can save an organization time and effort if the simulation is properly validated for the watershed, but will not provide the same degree of flexibility or transferability. Indeed, the practitioner should determine if the need and methods that resulted in the development of the hydrologic simulation are relevant to the asset valuation application, remembering that each model is built for a purpose and derived from choices made by the developer. The following is a non-exhaustive list of benefits of developing a hydrologic and/or water management model (i.e. using a climate baseline and starting the modeling chain at **Section 6.2** – From climate to hydrology instead of **Section 6.3** – From hydrology to energy).

The benefits of modeling inflow with a purpose-built hydrologic model include knowledge gained by the organization that can be transferred to other business activities (operations, project design, etc.). The hydrologic model can be used in other studies to identify the causes of trends in the hydrologic baseline (land-use changes, climate change, natural variability, etc.). This model can simultaneously account for multiple drivers, such as land-use changes and climate change, and analyze the relative influence of each one.

A water management model provides the ability to consider water management decisions, which may be implicit in the historic record (regulated) or may not be well represented in hydrologic simulations (naturalized, in most instances). Operator decisions, new infrastructure and changes in regulatory regimes can change historic outcomes on managed river systems. These influences should be considered not only in baseline selection, but also when preparing simulations and scenarios, as the historic flow or energy may not be a representative baseline. Also, using a water management model with an optimization routine to route historic inflows could result in deviations from past operations if using the hydrologic baseline. The inclusion of a water management model allows for the application of a consistent set of operations and rules to the entire period (reference and future). It also allows the operational rules/limits to be modified to accommodate potential changes in conditions, regulatory regimes or water availability under climate change. For dam-safety considerations, the ICOLD recommends reoperation of reservoirs as a first adaptation step (ICOLD, 2016).

Conclusion

In conclusion, the Guidebook provides guidance for the integration of climate change impacts in the value of hydropower assets. Section 1 provides a quick way to explore the possible links between climate change impacts and the valuation of an asset. Moreover, it identifies the need to develop methods to integrate climate change impacts in other climate-sensitive subcomponents of asset value other than energy and revenues, such as the provision of power and ancillary services, electricity demand, cost of action, cost of inaction, external costs and useful life of assets.

Sections 2 to 7, as well as the appendices, present various methods for integrating climate change data into asset valuation, along with their advantages and disadvantages. These provide the practitioner with alternatives to the traditional practice of using the hydrologic baseline to project the future. The practitioner is encouraged to choose the method most appropriate to particular watershed systems, organizational structure and practices, the availability of climatic and hydrologic information, and other elements. Another factor influencing the choice of method is how best to balance other uncertainties surrounding business decisions. The options can also be used in a complementary way, starting with the less comprehensive and then refining the analyses.

In the process of creating the Guidebook, a case study with each hydroelectric partner was carried out. To conclude, we would like to share some experiences and advice related to the various case studies.

The several options presented in this Guidebook, as well as the introduction of concepts and information, can be overwhelming, particularly for anyone new to climate change studies. As Guillaume Jean Tarel, neighbouring power networks advisor at Hydro-Québec put it: "It is not at all trivial and there is a relatively high risk of making conclusions using data that are not fit for purpose." For this reason, we suggest that practitioners with little or no experience in this area secure appropriate professional help.

The potential complexity and challenges along the modeling chain can cause practitioners to get stuck on technical details and lose sight of the big picture. When this situation arose during the Ontario Power Generation case study, Kurt C. Kornelsen, Senior Manager in Water Resources, said: "Let's complete the whole modeling chain first with the available information. If climate change has a meaningful influence on the value of the asset, then we can refine the assessment."

Finally, the amount of results and the acknowledged uncertainty surrounding climate change can prevent decision-makers from acting. On this point, Marie-Claude Simard, the Head of expertise in Hydraulics and Hydrology and responsible for climate change adaptation at Hydro-Québec Production, advises: "We need to show what is clear and undeniable about climate change, not just what is uncertain."

References

Abbasnezhadi, K. (2017). *Influence of Meteorological Network Density on Hydrological Modeling Using Input from the Canadian Precipitation Analysis (CaPA)* [Doctoral dissertation, University of Mantitoba]. **https://mspace.lib.umanitoba.ca/handle/1993/32177**

Agbazo, M. N., and Grenier, P. (2019). Characterizing and avoiding physical inconsistency generated by the application of univariate quantile mapping on daily minimum and maximum temperatures over Hudson Bay. *International Journal of Climatology*, 1–17. **https://doi.org/10.1002/joc.6432**

Arnell, N. W., and Gosling, S. N. (2013). The impacts of climate change on river flow regimes at the global scale. *Journal of Hydrology*, 486, 351–364. **https://doi.org/10.1016/j.jhydrol.2013.02.010**

Arsenault, R., Brissette, F., Malo, J. S., Minville, M., and Leconte, R. (2013). Structural and Non-Structural Climate Change Adaptation Strategies for the Péribonka Water Resource System. *Water Resources Management*, 27, 2075–2087. **https://doi.org/10.1007/s11269-013-0275-6**

Arsenault, R., Brissette, F., and Martel, J. L. (2018). The hazards of split-sample validation in hydrological model calibration. *Journal of Hydrology*, 566, 346–362. **https://doi.org/10.1016/j.jhydrol.2018.09.027**

Arsenault, R., Essou, G. R. C., and Brissette, F. P. (2017). Improving hydrological model simulations with combined multi-input and multimodel averaging frameworks. *Journal of Hydrologic Engineering*, 22(4), 04016066–04016061. **https://doi.org/10.1061/(ASCE)HE.1943-5584.0001489**

Arsenault, R., Gatien, P., Renaud, B., Brissette, F., and Martel, J. L. (2015). A comparative analysis of 9 multi-model averaging approaches in hydrological continuous streamflow simulation. *Journal of Hydrology*, 529, 754–767. **https://doi.org/10.1016/j.jhydrol.2015.09.001**

Bastola, S., Murphy, C., and Sweeney, J. (2011). The role of hydrological modelling uncertainties in climate change impact assessments of Irish river catchments. *Advances in Water Resources*, 34(5), 562–576. **https://doi.org/10.1016/j.advwatres.2011.01.008**

Benedetti, B., Fournier, E., Lamy, A., Pineault, K., and Hannart, A. (2018, October 18). *Ouranos workshop with Brookfield Renewable Power Workshop* [Workshop]. Series of workshop for Ouranos Project – Integrating climate change impacts in the valuation of hydroelectric assets, Gatineau, ON, Canada.

Bennett, T. H., and Peters, J. C. (2004). Continuous soil moisture accounting in the Hydrologic Engineering Center Hydrologic Modeling System (HEC-HMS). *Joint Conference on Water Resource Engineering and Water Resources Planning and Management 2000: Building Partnerships, 104*. **https://doi.org/10.1061/40517(2000)149**

Bergstrm, S., Lindstrm, G., and Pettersson, A. (2002). Multi-variable parameter estimation to increase confidence in hydrological modelling. *Hydrological Processes, 16*(2), 413–421. **https://doi.org/10.1002/hyp.332**

Beven, K. J. (2011). *Rainfall-runoff modelling: the primer* (2nd ed.). Wiley and Sons.

Blanchet, R., Le Blanc, M., Letellier, M., Lévesque, F., Geffray, F., Pineault, K., Fournier, E., Lamy, A., and Hannart, A. (2018, October 30). *Ouranos workshop with Innergex Renewable Energy Inc.* [Workshop]. Series of workshop for Ouranos Project – Integrating climate change impacts in the valuation of hydroelectric assets, Longueuil, QC, Canada.

Bosshard, T., Carambia, M., Goergen, K., Kotlarski, S., Krahe, P., Zappa, M., and Schär, C. (2013). Quantifying uncertainty sources in an ensemble of hydrological climate-impact projections. *Water Resources Research, 49*(3), 1523–1536. **https://doi.org/10.1029/2011WR011533**

Boyle, J., Cunningham, M., and Dekens, J. (2013). *Climate Change Adaptation and Canadian Infrastructure*. International Institute for Sustainable Development. **https://www.iisd.org/publications/climate-change-adaptation-and-canadian-infrastructure-review-literature**

Broderick, C., Matthews, T., Wilby, R. L., Bastola, S., and Murphy, C. (2016). Transferability of hydrological models and ensemble averaging methods between contrasting climatic periods. *Water Resources Research, 52*(10), 8343–8373. **https://doi.org/10.1002/2016WR018850**

C. Kornelsen, K., Helc, S., MacLeod, G., McDonald, M., Sajid, A., Pineault, K., Fournier, E., and Lamy, A. (2019, March 1). *Ouranos workshop with Ontario Power Generation* [Workshop]. Series of workshop for Ouranos Project – Integrating climate change impacts in the valuation of hydroelectric assets, Toronto, ON, Canada.

Canadian Electricity Association. (2016). *Adapting to climate change state of play and recommandations for electricity sector in Canada*. **https://electricity.ca/library/adapting-climate-change-state-play-recommendations-electricity-sector-canada/**

Cannon, A. J., Sobie, S. R., and Murdock, T. Q. (2015). Bias Correction of GCM Precipitation by Quantile Mapping: How Well Do Methods Preserve Changes in Quantiles and Extremes? *Journal of Climate, 28*(17), 6938–6959. **https://doi.org/10.1175/JCLI-D-14-00754.1**

Cao, W., Bowden, W. B., Davie, T., and Fenemor, A. (2006). Multi-variable and multi-site calibration and validation of SWAT in a large mountainous catchment with high spatial variability. *Hydrological Processes, 20*(5), 1057–1073. **https://doi.org/10.1002/hyp.5933**

Caron-Périgny, P.-O., Crobeddu, É., Émiel, G., Maldonado, J.-P., Ribichesi, C., Rousseau, S., Rondeau, P.-M., Simard, M.-C., Tarel, G. J., Pineault, K., Fournier, E., and Lamy, A. (2019, February 11 – 12). *Ouranos workshop with Hydro-Québec* [Workshop]. Series of workshop for Ouranos Project – Integrating climate change impacts in the valuation of hydroelectric assets, Montréal, QC, Canada.

Carter, T. R., Alfsen, K., Barrow, E., Bass, B., Dai, X., Desanker, P., Gaffin, S. R., Giorgi, F., Hulme, M., Lal, M., Mata, L. J., Mearns, L. O., Mitchell, J. F. B., Morita, T., Moss, R., Murdiyarso, D., Pabon-Caicedo, J. D., Palutikof, J., Parry, M. L., ... Scholes, R. J. (2007). *General Guidelines on the Use of Scenario Data for Climate Impact and Adaptation Assessment*. IPCC. **http://www.ipcc-data.org/guidelines/TGICA_guidance_sdciaa_v2_final.pdf**

Casajus, N., Périé, C., Logan, T., Lambert, M.-C., De Blois, S., and Berteaux, D. (2016). An Objective Approach to Select Climate Scenarios when Projecting Species Distribution under Climate Change. *PloS One, 11*(3), e0152495. **https://doi.org/10.1371/journal.pone.0152495**

Charron, I. (2016). *A guidebook on climate scenarios: Using climate information to guide adaptation research and decisions, 2016 edition*. Ouranos. **https://www.ouranos.ca/publication-scientifique/Guidebook-2016.pdf**

Chen, J., Arsenault, R., Brissette, F. P., Côté, P., and Su, T. (2019). Coupling annual, monthly and daily weather generators to simulate multisite and multivariate climate variables with low-frequency variability for hydrological modelling. *Climate Dynamics, 53*(7–8), 3841–3860. **https://doi.org/10.1007/s00382-019-04750-z**

Chen, J., Brissette, F. P., Chaumont, D., and Braun, M. (2013a). Finding appropriate bias correction methods in downscaling precipitation for hydrologic impact studies over North America. *Water Resources Research*, 49(7), 4187–4205. **https://doi.org/10.1002/wrcr.20331**

Chen, J., Brissette, F. P., Chaumont, D., and Braun, M. (2013b). Performance and uncertainty evaluation of empirical downscaling methods in quantifying the climate change impacts on hydrology over two North American river basins. *Journal of Hydrology*, 479, 200–214. **https://doi.org/10.1016/j.jhydrol.2012.11.062**

Chen, J., Brissette, F. P., and Leconte, R. (2011). Uncertainty of downscaling method in quantifying the impact of climate change on hydrology. *Journal of Hydrology*, 401(3–4), 190–202. **https://doi.org/10.1016/j.jhydrol.2011.02.020**

Chen, J., Brissette, F. P., and Lucas-Picher, P. (2016). Transferability of optimally-selected climate models in the quantification of climate change impacts on hydrology. *Climate Dynamics, 47*(9–10), 3359–3372. https://doi.org/10.1007/s00382-016-3030-x

Chen, J., Brissette, F. P., Lucas-Picher, P., and Caya, D. (2017). Impacts of weighting climate models for hydro-meteorological climate change studies. *Journal of Hydrology*, 549, 534–546. https://doi.org/10.1016/j.jhydrol.2017.04.025

Chen, J., Brissette, F. P., Poulin, A., and Leconte, R. (2011). Overall uncertainty study of the hydrological impacts of climate change for a Canadian watershed. *Water Resources Research, 47*(12), 1–16. https://doi.org/10.1029/2011WR010602

Cloutier, C., Geertsema, M., Jacob, M., and Schnorbus, M. (2016, October 2–5). *Summary of the report Potential Impacts of Climate Change on Lanslides Occurence in Canada* [Conference paper]. Canadian Geotechnical 69th Conference – GeoVancouver 2016, Vancouver, BC, Canada. https://www.researchgate.net/publication/312612487_Summary_of_the_report_Potential_Impacts_of_Climate_Change_on_Landslides_Occurrence_in_Canada

Coron, L., Andréassian, V., Bourqui, M., Perrin, C., and Hendrickx, F. (2011, 28 June – 7 July 2011). Pathologies of hydrological models used in changing climatic conditions: a review. In C.C. Ray Cas (Chair), *Earth on the Edge: Science for a Sustainable Planet* [Symposium]. XXV IUGG General Assembly, Melbourne, Vic, Australia. https://iahs.info/uploads/dms/16759.10-39-44-344-19-CoronACCEPTED_JH02-FINAL-WITH-MODIF.pdf

Coron, L., Andréassian, V., Perrin, C., Lerat, J., Vaze, J., Bourqui, M., and Hendrickx, F. (2012). Crash testing hydrological models in contrasted climate conditions: An experiment on 216 Australian catchments. *Water Resources Research, 48*(5), 1–17. https://doi.org/10.1029/2011WR011721

Davison, B., Pietroniro, A., Fortin, V., Leconte, R., Mamo, M., and Yau, M. K. (2016). What is missing from the prescription of hydrology for land surface schemes? *Journal of Hydrometeorology, 17*(7), 2013–2039. https://doi.org/10.1175/JHM-D-15-0172.1

De Niel, J., Van Uytven, E., and Willems, P. (2019). Uncertainty Analysis of Climate Change Impact on River Flow Extremes Based on a Large Multi-Model Ensemble. *Water Resources Management, 33*(12), 4319–4333. https://doi.org/10.1007/s11269-019-02370-0

Deser, C., Knutti, R., Solomon, S., and Phillips, A. S. (2012). Communication of the role of natural variability in future North American climate. *Nature Climate Change, 2*(11), 775–779. https://doi.org/10.1038/nclimate1562

Deser, C., Phillips, A. S., Alexander, M. A., and Smoliak, B. V. (2014). Projecting North American climate over the next 50 years: Uncertainty due to internal variability. *Journal of Climate, 27*(6), 2271–2296. **https://doi.org/10.1175/JCLI-D-13-00451.1**

Deser, C., Phillips, A. S., Bourdette Vincent, and Teng, H. (2012). Uncertainty in climate change projections: the role of internal variability. *Climate Dynamics*, 38, 527–546. **https://doi.org/10.1007/s00382-010-0977-x**

Diaconescu, E. P., Mailhot, A., Brown, R., and Chaumont, D. (2018). Evaluation of CORDEX-Arctic daily precipitation and temperature-based climate indices over Canadian Arctic land areas. *Climate Dynamics, 50*(5–6), 2061–2085. **https://doi.org/10.1007/s00382-017-3736-4**

Evin, G., Hingray, B., Blanchet, J., Eckert, N., Morin, S., and Verfaillie, D. (2019). Partitioning uncertainty components of an incomplete ensemble of climate projections using data augmentation. *Journal of Climate, 32*(8), 2423–2440. **https://doi.org/10.1175/JCLI-D-18-0606.1**

Eyring, V., Bony, S., Meehl, G. A., Senior, C. A., Stevens, B., Stouffer, R. J., and Taylor, K. E. (2016). Overview of the Coupled Model Intercomparison Project Phase 6 (CMIP6) experimental design and organization. *Geoscientific Model Development, 9*(5), 1937–1958. **https://doi.org/10.5194/gmd-9-1937-2016**

Feng, D. (2018). *Characterizing Changes in Hydrologic Fluxes and Uncertainties for Current and Future Climate Conditions* [Doctoral dissertation, Northeastern University]. **https://repository.library.northeastern.edu/files/neu:m044c4807**

Fischer, E. M., Beyerle, U., and Knutti, R. (2013). Robust spatially aggregated projections of climate extremes. *Nature Climate Change, 3*(12), 1033–1038. **https://doi.org/10.1038/nclimate2051**

Fleming, M., and Neary, V. (2004). Continuous Hydrologic Modeling Study with the Hydrologic Modeling System. *Journal of Hydrologic Engineering, 9*(3), 175–183. **https://doi.org/10.1061/(ASCE)1084-0699(2004)9:3(175)**

Forrest, K., Tarroja, B., Chiang, F., AghaKouchak, A., and Samuelson, S. (2018). Assessing climate change impacts on California hydropower generation and ancillary services provision. *Climatic Change, 151*(3–4), 395–412. **https://link.springer.com/article/10.1007/s10584-018-2329-5**

Fournier, É., Braun, B. Merleau, J., Simard, M.C. (2015). *Concordance entre les sorties directes et post-traitées de l'ensemble CMIP5 et les données NRCAN selon certaines caractéristiques statistiques calculées à l'échelle des bassins versants du complexe Manicouagan* [Internal report]. Ouranos project Montréal, QC, Canada.

Fournier, É. Merleau, J. (2016). *Concordance entre les données sur grille NRCan et MDDELCC et les données du projet CROQ selon les caractéristiques statistiques calculées à l'échelle des bassins versants du complexe Manicouagan* [Internal report]. Ouranos project Montréal, QC, Canada.

François, B., Schlef, K. E., Wi, S., and Brown, C. M. (2019). Design considerations for riverine floods in a changing climate – A review. *Journal of Hydrology*, 574, 557–573. **https://doi.org/10.1016/j.jhydrol.2019.04.068**

Gao, J., Sheshukov, A. Y., Yen, H., Douglas-Mankin, K. R., White, M. J., and Arnold, J. G. (2019). Uncertainty of hydrologic processes caused by bias-corrected CMIP5 climate change projections with alternative historical data sources. *Journal of Hydrology*, 568, 551–561. **https://doi.org/10.1016/j.jhydrol.2018.10.041**

Gennaretti, F., Sangelantoni, L., and Grenier, P. (2015). Toward daily climate scenarios for Canadian Arctic coastal zones with more realistic temperature-precipitation interdependence. *Journal of Geophysical Research: Atmospheres, 120*(23). **https://doi.org/10.1002/2015JD023890**

Giuntoli, I, Vidal, J. P., Prudhomme, C., and Hannah, D. M. (2015). Future hydrological extremes: The uncertainty from multiple global climate and global hydrological models. *Earth System Dynamics, 6*(1), 267–285. **https://doi.org/10.5194/esd-6-267-2015**

Giuntoli, Ignazio, Villarini, G., Prudhomme, C., and Hannah, D. M. (2018). Uncertainties in projected runoff over the conterminous United States. *Climatic Change*, 150, 149–162. **https://doi.org/10.1007/s10584-018-2280-5**

Groulx, F., Chavaillaz, Y., Mercier, V., Sparks, D., Fournier, E., and Pineault, K. (2019, May 31). *Ouranos interview with WSP* [Interview]. Series of interview for Ouranos Project – Integrating climate change impacts in the valuation of hydroelectric assets, Montréal, QC, Canada

Guay, C., Minville, M., and Braun, M. (2015). A global portrait of hydrological changes at the 2050 horizon for the province of Québec. *Canadian Water Resources Journal, 40*(3), 285-302. **https://doi.org/10.1080/07011784.2015.1043583**

Gupta, HV, Bastidas, LA, Sorooshian, S, Shuttleworth, WJ, Yang, Z. L. (1999). Parameter estimation of a land surface scheme using multicriteria methods. *Journal of Geophysical Research, 104*(D16), 19,419-491,503. **https://doi.org/10.1029/1999JD900154**

Haerter, J. O., Hagemann, S., Moseley, C., and Piani, C. (2011). Hydrology and Earth System Sciences Climate model bias correction and the role of timescales. *Hydrol. Earth Syst. Sci, 15*, 1065–1079. **https://doi.org/10.5194/hess-15-1065-2011**

Haguma, D., Leconte, R., and Krau, S. (2017). Hydropower plant adaptation strategies for climate change impacts on hydrological regime. *Can. J. Civ. Eng., 44*, 962–970. **https://doi.org/10.1139/cjce-2017-0141**

Hajji, I., Nadeau, D. F., Music, B., Anctil, F., and Wang, J. (2018). Application of the maximum entropy production model of evapotranspiration over partially vegetated water-limited land surfaces. *Journal of Hydrometeorology, 19*(6), 989–1005. **https://doi.org/10.1175/JHM-D-17-0133.1**

Hanrahan, J. L., Kravtsov, S. V., and Roebber, P. J. (2010). Connecting past and present climate variability to the water levels of Lakes Michigan and Huron. *Geophysical Research Letters, 37*(1), 1–6. **https://doi.org/10.1029/2009GL041707**

Hattermann, F. F., Vetter, T., Breuer, L., Su, B., Daggupati, P., Donnelly, C., Fekete, B., Florke, F., Gosling, S. N., Hoffmann, P., Liersch, S., Masaki, Y., Motovilov, Y., Muller, C., Samaniego, L., Stacke, T., Wada, Y., Yang, T., and Krysnaova, V. (2018). Sources of uncertainty in hydrological climate impact assessment: A cross-scale study. *Environmental Research Letters, 13*(1). **https://doi.org/10.1088/1748-9326/aa9938**

Hausfather, Z. (2018, April 19). *Explainer: How 'Shared Socioeconomic Pathways' explore future climate change*. Carbon Brief. **https://www.carbonbrief.org/explainer-how-shared-socioeconomic-pathways-explore-future-climate-change**

Hawkins, E., Smith, R. S., Gregory, J. M., and Stainforth, D. A. (2016). Irreducible uncertainty in near-term climate projections. *Climate Dynamics, 46*(11–12), 3807–3819. **https://doi.org/10.1007/s00382-015-2806-8**

Hawkins, E., and Sutton, R. (2009). The Potential to Narrow Uncertainty in Regional Climate Predictions. *Bulletin American Meteorological Society, 90*(8), 1095–1107. **https://doi.org/10.1175/2009BAMS2607.1**

Hawkins, E., and Sutton, R. (2011). The potential to narrow uncertainty in projections of regional precipitation change. *Climate Dynamics, 37*(1), 407–418. **https://doi.org/10.1007/s00382-010-0810-6**

Hayhoe, H. N. (2000). Improvements of stochastic weather data generators for diverse climates. *Climate Research, 14*(2), 75–87. **https://doi.org/10.3354/cr014075**

Hegerl, G. C., Hoegh-Guldberg, O., Casassa, G., Hoerling, M., Kovats, S., Parmesan, C., Pierce, D., and Stott, P. (2010). *Good practice guidance paper on detection and attribution related to anthropogenic climate change.* IPCC Working Group I Technical Support Unit. **https://wg1.ipcc.ch/docs/IPCC_D&A_GoodPracticeGuidancePaper-1.pdf**

Hegerl, G. C., Zwiers, F. W., Braconnot, P., Gillett, N. P., Luo, Y., Marengo Orsini Brazil, J. A., Nicholls, N., Penner, J. E., Stott, P. A., Karoly USA, D. J., Ogallo, L., Planton, S., Zwiers, F. W., Braconnot, P., Gillett, N., Luo, Y., Marengo Orsini, J., Nicholls, N., Penner, J., … Tignor, M. (2007). Understanding and Attributing Climate. In M. T. and H. L. M. Solomon, S., D. Qin, M. Manning, Z. Chen, M. Marquis, K.B. Averyt (Eds.), *Climate Change 2007: The Physical Science Basis. Contribution of Working Group I to the Fourth Assessment Report of the Intergovernmental Panel on Climate Change* (pp. 663–745). Cambridge University Press.

Hempel, S., Frieler, K., Warszawski, L., Schewe, J., and Piontek, F. (2013). A trend-preserving bias correction – the ISI-MIP approach. *Earth System Dynamics, 4*(2), 219–236. **https://doi.org/10.5194/esd-4-219-2013**

Her, Y., Yoo, S. H., Cho, J., Hwang, S., Jeong, J., and Seong, C. (2019). Uncertainty in hydrological analysis of climate change: multi-parameter vs. multi-GCM ensemble predictions. *Nature Scientific Reports, 9*(1), 1–22. **https://doi.org/10.1038/s41598-019-41334-7**

Hingray, B., Musy, A., and Picouet, C. (2015). *Hydrology: a science for engineers*. CRC Press.

Horner, I., Renard, B., Le Coz, J., Branger F., McMillan, H.K., Pierrefeu, G. (2018). Impact of Stage Measurement Errors on Streamflow Uncertainty. *Water Resources Research, 54*(3), 1952-1976. **https://doi.org/10.1002/2017WR022039**

Hosseinzadehtalaei, P., Tabari, H., and Willems, P. (2017). Uncertainty assessment for climate change impact on intense precipitation: how many model runs do we need? *International Journal of Climatology, 37*, 1105–1117. **https://doi.org/10.1002/joc.5069**

Hrachowitz, M., Savenije, H. H. G., Blöschl, G., McDonnell, J. J., Sivapalan, M., Pomeroy, J. W., Arheimer, B., Blume, T., Clark, M. P., Ehret, U., Fenicia, F., Freer, J. E., Gelfan, A., Gupta, H. V., Hughes, D. A., Hut, R. W., Montanari, A., Pande, S., Tetzlaff, D., … Cudennec, C. (2013). A decade of Predictions in Ungauged Basins (PUB)—a review. *Hydrological Sciences Journal, 58*(6), 1198–1255. **https://doi.org/10.1080/02626667.2013.803183**

Hunukumbura, P. B., Tachikawa, Y., and Shiiba, M. (2012). Distributed hydrological model transferability across basins with different hydro-climatic characteristics. *Hydrological Processes, 26*(6), 793–808. **https://doi.org/10.1002/hyp.8294**

Hutchinson, M. F., McKenney, D. W., Lawrence, K., Pedlar, J. H., Hopkinson, R. F., Milewska, E., and Papadopol, P. (2009). Development and Testing of Canada-Wide Interpolated Spatial Models of Daily Minimum–Maximum Temperature and Precipitation for 1961–2003. *Journal of Applied Meteorology and Climatology, 48*(4), 725–741. **https://doi.org/10.1175/2008JAMC1979.1**

ICOLD. (2016). *Bulletin 169: Global Climate Change, Dams, Reservoirs and Related Water Resources*. International Commission On Large Dams.

IHA. (2019). *Hydropower Sector Climate Resilience Guide*. International Hydropower Association. **https://www.hydropower.org/publications/hydropower-sector-climate-resilience-guide**

Immerzeel, W. W., and Droogers, P. (2008). Calibration of a distributed hydrological model based on satellite evapotranspiration. *Journal of Hydrology, 349*(3–4), 411–424. **https://doi.org/10.1016/j.jhydrol.2007.11.017**

IPCC. (2007). *Climate Change 2007: Synthesis Report. Contribution of Working Groups I, II and III to the Fourth Assessment Report of the Intergovernmental Panel on Climate Change* (Core Writing Team, R.K. Pachauri, and A. Reisinger, Eds.). IPCC. **https://www.ipcc.ch/site/assets/uploads/2018/02/ar4_syr_full_report.pdf**

IPCC. (2014). *Climate change 2013: The physical science basis: Working Group I contribution to the fifth assessment report of the intergovernmental panel on climate change*. Cambridge University Press. **https://doi.org/10.1017/CBO9781107415324**

IPCC. (2014). *Climate Change 2014: Synthesis Report. Contribution of Working Groups I, II and III to the Fifth Assessment Report of the Intergovernmental Panel on Climate Change* (Core Writing Team, R. K. Pachauri, and L.A. Meyer (Eds.). IPCC. **https://doi.org/10.1017/CBO9781107415324.031**

Isaac, M., and Van Vuuren, D. P. (2009). Modeling global residential sector energy demand for heating and air conditioning in the context of climate change. *Energy Policy, 37*(2), 507–521. **https://doi.org/10.1016/j.enpol.2008.09.051**

Jaglom, W. S., McFarland, J. R., Colley, M. F., Mack, C. B., Venkatesh, B., Miller, R. L., Haydel, J., Schultz, P. A., Perkins, B., Casola, J. H., Martinich, J. A., Cross, P., Kolian, M. J., and Kayin, S. (2014). Assessment of projected temperature impacts from climate change on the U.S. electric power sector using the Integrated Planning Model®. *Energy Policy, 73*, 524–539. **https://doi.org/10.1016/j.enpol.2014.04.032**

Jie, M. X., Chen, H., Xu, C. Y., Zeng, Q., Chen, J., Kim, J. S., lian Guo, S., and Guo, F. Q. (2018). Transferability of Conceptual Hydrological Models Across Temporal Resolutions: Approach and Application. *Water Resources Management, 32*(4), 1367–1381. **https://doi.org/10.1007/s11269-017-1874-4**

Jones, R. N. (2000). Managing uncertainty in climate change projections–issues for impact assessment. *Climatic Change, 45*(3), 403–419. **https://doi.org/10.1016/j.urology.2013.09.061**

Kao, S. C., Sale, M. J., Ashfaq, M., Uria Martinez, R., Kaiser, D. P., Wei, Y., and Diffenbaugh, N. S. (2015). Projecting changes in annual hydropower generation using regional runoff data: An assessment of the United States federal hydropower plants. *Energy, 80*, 239–250. https://doi.org/10.1016/j.energy.2014.11.066

Kay, A. L., Davies, H. N., Bell, V. A., and Jones, R. G. (2009). Comparison of uncertainty sources for climate change impacts: Flood frequency in England. *Climatic Change, 92*(1–2), 41–63. https://doi.org/10.1007/s10584-008-9471-4

Khadam, I. M., and Kaluarachchi, J. J. (2004). Use of soft information to describe the relative uncertainty of calibration data in hydrologic models. *Water Resources Research, 40*(11). https://doi.org/10.1029/2003WR002939

Kim, K., Park, T., Bang, S., and Kim, H. (2017). Real Options-Based Framework for Hydropower Plant Adaptation to Climate Change. *Journal of Management in Engineering, 33*(3), 04016049. https://doi.org/10.1061/(ASCE)ME.1943-5479.0000496

King, L. M., McLeod, A. I., and Simonovic, S. P. (2014). Simulation of historical temperatures using a multi-site, multivariate block resampling algorithm with perturbation. *Hydrological Processes, 28*(3), 905–912. https://doi.org/10.1002/hyp.9596

Klein, S. A., and Hall, A. (2015). Emergent Constraints for Cloud Feedbacks. *Current Climate Change Reports, 1*, 276–287. https://doi.org/10.1007/s40641-015-0027-1

KlemeŠ, V. (1986). Operational testing of hydrological simulation models. *Hydrological Sciences Journal, 31*(1), 13–24. https://doi.org/10.1080/02626668609491024

Knutti, R., Masson, D., and Gettelman, A. (2013). Climate model genealogy: Generation CMIP5 and how we got there. *Geophysical Research Letters, 40*(6), 1194–1199. https://doi.org/10.1002/grl.50256

Krysanova, V., Donnelly, C., Gelfan, A., Gerten, D., Arheimer, B., Hattermann, F., Kundzewicz, Z. W., and Di Baldassarre, G. (2018). How the performance of hydrological models relates to credibility of projections under climate change. *Hydrological Sciences Journal, 63*(5), 679–720. https://doi.org/10.1080/02626667.2018.1446214

Kumarasamy, K., and Belmont, P. (2018). Calibration parameter selection and watershed hydrology model evaluation in time and frequency domains. *Water, 10*(6), 710. https://doi.org/10.3390/w10060710

Lafrance, G., Da Silva, L., and Desjarlais, C. (2016). *Impact des changements climatiques sur la demande d'énergie*. Ouranos. **https://www.ouranos.ca/publication-scientifique/RapportLafrance2016.pdf**

Lofgren, B. M., Hunter, T. S., and Wilbarger, J. (2011). Effects of using air temperature as a proxy for potential evapotranspiration in climate change scenarios of Great Lakes basin hydrology. *Journal of Great Lakes Research, 37*(4), 744–752. **https://doi.org/10.1016/j.jglr.2011.09.006**

Ludwig, R., Chartier, I., Caya, D., Mauser, W., May, I., Turcotte, R., Vescovi, L., Braun, M., Cyr, J.-F., Fortin, L.-G., Chaumont, D., and Biner, S. (2009). The role of hydrological model complexity and uncertainty in climate change impact assessment. *Advances in Geosciences, 21*(Journal Article), 63–71. **https://doi.org/10.5194/adgeo-21-63-2009**

Luke, Adam;Vrugt, Jasper A.;AghaKouchak, Amir; Matthew, Richard; Sanders, B. F. (2017). Predicting nonstationary flood frequencies: Evidence supports an updated stationarity thesis in the United States. *Water Resources Research, 53*, 5469–5494. **https://doi.org/10.1002/ 2016WR019676**

Madani, K., and Lund, J. R. (2010). Estimated impacts of climate warming on California's high-elevation hydropower. *Climatic Change, 102*(3–4), 521–538. **https://doi.org/10.1007/s10584-009-9750-8**

Magand, C. (2014). *Influence de la représentation des processus nivaux sur l'hydrologie de la Durance et sa réponse au changement climatique* [Doctoral dissertation, Université Pierre et Marie Curie – Paris VI]. **https://tel.archives-ouvertes.fr/tel-01027409**

Mahfouf, J. F., Brasnett, B., and Gagnon, S. (2007). A Canadian precipitation analysis (CaPA) project: Description and preliminary results. *Atmosphere – Ocean, 45*(1), 1–17. **https://doi.org/10.3137/ao.v450101**

Malovic, D., Engelmann-Pilger, H., Arsenijevic, N., Gassner, K. B., Merle-Beral, E., Monti, G., Pooley, J., Inouye, L. K., Levin, J., and Kellenberg, J. (2015). *Hydroelectric Power: A Guide for Developers and Investors*. World Bank Group. **https://www.ifc.org/wps/wcm/connect/topics_ext_content/ifc_external_corporate_site/sustainability-at-ifc/publications/hydroelectric_power_a_guide_for_developers_and_investors**

Mandal, S., and Simonovic, S. P. (2017). Quantification of uncertainty in the assessment of future streamflow under changing climate conditions. *Hydrological Processes, 31*(11), 2076–2094. **https://doi.org/10.1002/hyp.11174**

Manitoba Hydro. (2013). *Need For and Alternatives To, Chapter 10 – Economic uncertainty analysis – Probabilistic Analysis and Sensitivities*. Manitoba Hydro. http://www.pubmanitoba.ca/v1/nfat/pdf/hydro_application/nfat_business_case_chapter_10_economic_uncertainty_analysis_probabilistic_analysis_and_sensitivities.pdf

Manitoba Hydro. (2015). *Projected Climate Change Impacts on Energy and Peak Demand in Manitoba* Natural Resources Canada, Climate Change Impacts and Adaptation Division. https://www.prairiesrac.com/wp-content/uploads/2018/06/Projected-Climate-Change-Impacts-on-Energy-and-Peak-Demand-in-Manitoba-MB-Hydro.pdf

Maraun, D., Shepherd, T. G., Widmann, M., Zappa, G., Walton, D., Gutiérrez, J. M., Hagemann, S., Richter, I., Soares, P. M. M., Hall, A., and Mearns, L. O. (2017). Towards process-informed bias correction of climate change simulations. *Nature Climate Change, 7*(11), 764–773. https://doi.org/10.1038/nclimate3418

Maraun, D., and Widmann, M. (Martin L. (2018). *Statistical downscaling and bias correction for climate research*. Cambridge University Press.

Maréchal, D., and Holman, I. P. (2004, July 1). *Comparison of Hydrologic Simulations using Regionalised and Catchment-Calibrated Parameter Sets for three Catchments in England* [Paper presentation]. 2nd International Congress on Environmental Modelling and Software, Osnabrück, Basse-Saxe, Germany. https://scholarsarchive.byu.edu/iemssconference/2004/all/219

Mendoza, G., Jeuken, A., Matthews, J. H., Stakhiv, E., Kucharski, J., and Gilroy, K. (2018). *Climate Risk Informed Decision Analysis (CRIDA): collaborative water resources planning for an uncertain future*. United Nations Educational, Scientific and Cultural Organization (UNESCO). https://unesdoc.unesco.org/ark:/48223/pf0000265895

Merz, R., Parajka, J., and Blöschl, G. (2011). Time stability of catchment model parameters: Implications for climate impact analyses. *Water Resources Research, 47*(2). https://doi.org/10.1029/2010WR009505

Mideksa, T. K., and Kallbekken, S. (2010). The impact of climate change on the electricity market: A review. *Energy Policy, 38*(7), 3579–3585.

Minville, M, Cartier, D., Guay, C., Leclaire, L.-A., Audet, C., Le Digabel, S., and Merleau, J. (2014). Improving process representation in conceptual hydrological model calibration using climate simulations. *Water Resources Research, 50*(6), 5044–5073. https://doi.org/10.1002/2013WR013857.Received

Minville, Marie, Brissette, F., Krau, S., and Leconte, R. (2009). Adaptation to climate change in the management of a Canadian water-resources system exploited for hydro-power. *Water Resources Management, 23*(14), 2965–2986. **https://doi.org/10.1007/s11269-009-9418-1**

Moss, R. H., Edmonds, J. a, Hibbard, K. a, Manning, M. R., Rose, S. K., van Vuuren, D. P., Carter, T. R., Emori, S., Kainuma, M., Kram, T., Meehl, G. a, Mitchell, J. F. B., Nakicenovic, N., Riahi, K., Smith, S. J., Stouffer, R. J., Thomson, A. M., Weyant, J. P., and Wilbanks, T. J. (2010). The next generation of scenarios for climate change research and assessment. *Nature, 463*(7282), 747–756. **https://doi.org/10.1038/nature08823**

Motavita, D. F., Chow, R., Guthke, A., and Nowak, W. (2019). The comprehensive differential split-sample test: A stress-test for hydrological model robustness under climate variability. *Journal of Hydrology, 573*, 501–515. **https://doi.org/10.1016/j.jhydrol.2019.03.054**

O'Neill, B. C., Kriegler, E., Riahi, K., Ebi, K. L., Hallegatte, S., Carter, T. R., Mathur, R., and van Vuuren, D. P. (2014). A new scenario framework for climate change research: The concept of shared socioeconomic pathways. *Climatic Change, 122*(3), 387–400. **https://doi.org/10.1007/s10584-013-0905-2**

O'Neill, B. C., Tebaldi, C., van Vuuren, D., Eyring, V., Friedlingstein, P., Hurtt, G., Knutti, R., Kriegler, E., Lamarque, J.-F., Lowe, J., Meehl, J., Moss, R., Riahi, K., and Sanderson, B. M. (2016). The Scenario Model Intercomparison Project (ScenarioMIP) for CMIP6. In *Geoscientific Model Development Discussions* (Issue 9, pp. 3461–3482). **https://doi.org/10.5194/gmd-2016-84**

Olden, J. D., and Poff, N. L. (2003). Redundancy and the choice of hydrologic indices for characterizing streamflow regimes. *River Research and Applications, 19*(2), 101–121. **https://doi.org/10.1002/rra.700**

Onyutha, C. (2019). Hydrological model supported by a step-wise calibration against sub-flows and validation of extreme flow events. *Water, 11*(2), 244. **https://doi.org/10.3390/w11020244**

Ouranos. (2015). *Ouranos Decision-Making Project*. **http://scenarios-decision.ouranos.ca/en**

Patil, S. D., and Stieglitz, M. (2015). Comparing spatial and temporal transferability of hydrological model parameters. *Journal of Hydrology, 525*, 409–417. **https://doi.org/10.1016/j.jhydrol.2015.04.003**

Pearl, J. (2009). *Causality: Models, Reasoning and inference* (2nd ed.). Cambridge University Press. **http://bayes.cs.ucla.edu/BOOK-2K/**

Pechlivanidis, I. G., Jackson, B. M., Mcintyre, N. R., and Wheater, H. S. (2011). Catchment scale hydrological modelling: A review of model types, calibration approaches and uncertainty analysis methods in the context of recent developments in technology and applications. *Global Nest Journal, 13*(3), 193–214. **https://doi.org/10.30955/gnj.000778**

Poulin, A., Brissette, F., Leconte, R., Arsenault, R., and Malo, J. S. (2011). Uncertainty of hydrological modelling in climate change impact studies in a Canadian, snow-dominated river basin. *Journal of Hydrology, 409*(3–4), 626–636. **https://doi.org/10.1016/j.jhydrol.2011.08.057**

Prudhomme, C., and Davies, H. (2009). Assessing uncertainties in climate change impact analyses on the river flow regimes in the UK. Part 2: Future climate. *Climatic Change, 93*(1–2), 197–222. **https://doi.org/10.1007/s10584-008-9461-6**

Randall, D. A., Wood, R. A., Bony, S., Colman, R., Fichefet, T., Fyfe, J., Kattsov, V., A. Pitman, J., Shukla, J., Srinivasan, R. J., Stouffer, A. S., and Taylor, K. E. (2007). Climate Models and Their Evaluation. In S. D. Solomon, D. Qin, M. Manning, Z. Chen, M. Marquis, K. B. Averyt, M. Tignor, and H. L. Miller (Eds.), *Climate Change 2007: The Physical Science Basis. Contribution of Working Group I to the Fourth Assessment Report of the Intergovernmental Panel on Climate Change* (Vol. 323, pp. 589–662). Cambridge University Press.

Razavi, T., and Coulibaly, P. (2013). Streamflow prediction in ungauged basins: Review of regionalization methods. *Journal of Hydrologic Engineering, 18*(8), 958–975. **https://doi.org/10.1061/(ASCE)HE.1943-5584.0000690**

Refsgaard, J. C., Madsen, H., Andréassian, V., Arnbjerg-Nielsen, K., Davidson, T. A., Drews, M., Hamilton, D. P., Jeppesen, E., Kjellström, E., Olesen, J. E., Sonnenborg, T. O., Trolle, D., Willems, P., and Christensen, J. H. (2014). A framework for testing the ability of models to project climate change and its impacts. *Climatic Change, 122*(1–2), 271–282. **https://doi.org/10.1007/s10584-013-0990-2**

Reynolds, J. E., Halldin, S., Xu, C. Y., Seibert, J., and Kauffeldt, A. (2017). Sub-daily runoff predictions using parameters calibrated on the basis of data with a daily temporal resolution. *Journal of Hydrology, 550*, 399–411. **https://doi.org/10.1016/j.jhydrol.2017.05.012**

Sagan, K., Driver, A., Gawne, K., Halayko, A., Teklemariam, E., Pineault, K., Fournier, E., and Lamy, A. (2019, May 22). *Ouranos workshop with Manitoba Hydro* [Workshop]. Series of workshop for Ouranos Project – Integrating climate change impacts in the valuation of hydroelectric assets, Winnipeg, MB, Canada.

Samaniego, L., Kumar, R., and Attinger, S. (2010). Multiscale parameter regionalization of a grid-based hydrologic model at the mesoscale. *Water Resources Research, 46*(5), 1–25. **https://doi.org/10.1029/2008WR007327**

Samaniego, L., Kumar, R., Thober, S., Rakovec, O., Zink, M., Wanders, N., Eisner, S., Müller Schmied, H., Sutanudjaja, E., Warrach-Sagi, K., and Attinger, S. (2017). Toward seamless hydrologic predictions across spatial scales. *Hydrology and Earth System Sciences, 21*(9), 4323–4346. **https://doi.org/10.5194/hess-21-4323-2017**

Sanderson, B. M., Knutti, R., and Caldwell, P. (2015). A Representative Democracy to Reduce Interdependency in a Multimodel Ensemble. *Journal of Climate, 28*(13), 5171–5194. **https://doi.org/10.1175/JCLI-D-14-00362.1**

Sanderson, B. M., Oleson, K. W., Strand, W. G., Lehner, F., and O'Neill, B. C. (2018). A new ensemble of GCM simulations to assess avoided impacts in a climate mitigation scenario. *Climatic Change, 146*(3–4), 303–318. **https://doi.org/10.1007/s10584-015-1567-z**

Savenije, H. H. G. (2004). The importance of interception and why we should delete the term evapotranspiration from our vocabulary. *Hydrological Processes, 18*(8), 1507–1511. **https://doi.org/10.1002/hyp.5563**

Schaefli, B. (2015). Projecting hydropower production under future climates: a guide for decision-makers and modelers to interpret and design climate change impact assessments. *Wiley Interdisciplinary Reviews: Water, 2*(4), 271–289. **https://doi.org/10.1002/wat2.1083**

Seiller, G., Anctil, F., and Perrin, C. (2012). Hydrology and Earth System Sciences. *European Geosciences Union, 16*(4), 1171–1189. **https://doi.org/10.5194/hess-1116-1171-2012ï**

Sellami, H., Benabdallah, S., La Jeunesse, I., and Vanclooster, M. (2016). Climate models and hydrological parameter uncertainties in climate change impacts on monthly runoff and daily flow duration curve of a Mediterranean catchment. *Hydrological Sciences Journal, 61*(8), 1415–1429. **https://doi.org/10.1080/02626667.2015.1040801**

Seo, S. B., Kim, Y. O., Kim, Y., and Eum, H. Il. (2019). Selecting climate change scenarios for regional hydrologic impact studies based on climate extremes indices. *Climate Dynamics, 52*(3–4), 1595–1611. **https://doi.org/10.1007/s00382-018-4210-7**

Shen, M., Chen, J., Zhuan, M., Chen, H., Xu, C. Y., and Xiong, L. (2018). Estimating uncertainty and its temporal variation related to global climate models in quantifying climate change impacts on hydrology. *Journal of Hydrology, 556*, 10–24. **https://doi.org/10.1016/j.jhydrol.2017.11.004**

Sillmann, J., Thorarinsdottir, T., Keenlyside, N., Schaller, N., Alexander, L. V, Hegerl, G., Seneviratne, S. I., Vautard, R., Zhang, X., and Zwiers, F. W. (2017). Understanding, modeling and predicting weather and climate extremes: Challenges and opportunities. *Weather and Climate Extremes, 18*, 68–74. **https://doi.org/10.1016/j.wace.2017.10.003**

Singh, R., Wagener, T., van Werkhoven, K., Mann, M. E., and Crane, R. (2011). A trading-space-for-time approach to probabilistic continuous streamflow predictions in a changing climate – accounting for changing watershed behavior. *Hydrology and Earth System Sciences, 15*(11), 3591–3603. **https://doi.org/10.5194/hess-15-3591-2011**

Snover, A. K., Hamlet, A. F., and Lettenmaier, D. P. (2003). Climate-Change Scenarios for Water Planning Studies: Pilot Applications in the Pacific Northwest. *Bulletin of the American Meteorological Society, 84*, 1513–1518. **https://doi.org/10.2307/26216902**

Stoll, B., Andrade, J., Cohen, S., Brinkman, G., and Brancucci Martinez-Anido, C. (2017). *Hydropower Modeling Challenges*. National Renewable Energy Lab. **https://doi.org/10.2172/1353003**

Taylor, K. E., Stouffer, R. J., and Meehl, G. A. (2012). An overview of CMIP5 and the experiment design. *Bulletin of the American Meteorological Society, 93*(4), 485–498. **https://doi.org/10.1175/BAMS-D-11-00094.1**

TCFD. (2017). Recommendations of the Task Force on Climate-related Financial Disclosures. Task Force on climate-related financial disclosures. https://www.fsb-tcfd.org/wp-content/uploads/2017/06/FINAL-2017-TCFD-Report-11052018.pdf

Thirel, G., Andréassian, V., and Perrin, C. (2015). De la nécessité de tester les modèles hydrologiques sous des conditions changeantes. *Hydrological Sciences Journal, 60*(7–8), 1165–1173. **https://doi.org/10.1080/02626667.2015.1050027**

Troin, M., Arsenault, R., Martel, J. L., and Brissette, F. (2018). Uncertainty of hydrological model components in climate change studies over two nordic quebec catchments. *Journal of Hydrometeorology, 19*(1), 27–46. **https://doi.org/10.1175/JHM-D-17-0002.1**

Van Uytven, E., and Willems, P. (2018). Greenhouse gas scenario sensitivity and uncertainties in precipitation projections for central Belgium. *Journal of Hydrology, 558*, 9–19. **https://doi.org/10.1016/j.jhydrol.2018.01.018**

Vetter, T., Reinhardt, J., Flörke, M., van Griensven, A., Hattermann, F., Huang, S., Koch, H., Pechlivanidis, I. G., Plötner, S., Seidou, O., Su, B., Vervoort, R. W., and Krysanova, V. (2017). Evaluation of sources of uncertainty in projected hydrological changes under climate change in 12 large-scale river basins. *Climatic Change, 141*(3), 419–433. **https://doi.org/10.1007/s10584-016-1794-y**

Vidal, J. P., Hingray, B., Magand, C., Sauquet, E., and Ducharne, A. (2016). Hierarchy of climate and hydrological uncertainties in transient low-flow projections. *Hydrology and Earth System Sciences, 20*(9), 3651–3672. **https://doi.org/10.5194/hess-20-3651-2016**

Wada, Y., Wisser, D., Eisner, S., Flörke, M., Gerten, D., Haddeland, I., Hanasaki, N., Masaki, Y., Portmann, F. T., Stacke, T., Tessler, Z., and Schewe, J. (2013). Multimodel projections and uncertainties of irrigation water demand under climate change. *Geophysical Research Letters, 40*(17), 4626–4632. **https://doi.org/10.1002/grl.50686**

Wagener, T., and Montanari, A. (2011). Convergence of approaches toward reducing uncertainty in predictions in ungauged basins. *Water Resources Research, 47*(6). **https://doi.org/10.1029/2010WR009469**

Wang, H. M., Chen, J., Cannon, A. J., Xu, C. Y., and Chen, H. (2018). Transferability of climate simulation uncertainty to hydrological impacts. *Hydrology and Earth System Sciences, 22*(7), 3739–3759. **https://doi.org/10.5194/hess-22-3739-2018**

Wilby, R. L. (2010). Evaluating climate model outputs for hydrological applications. *Hydrological Sciences Journal, 55*(7), 1090–1093. **https://doi.org/10.1080/02626667.2010.513212**

Wilby, R. L., and Harris, I. (2006). A framework for assessing uncertainties in climate change impacts: Low-flow scenarios for the River Thames, UK. *Water Resources Research, 42*(2), 1–10. **https://doi.org/10.1029/2005WR004065**

Wilks, D. ., and Wilby, R. . (1999). The weather generation game: a review of stochastic weather models. *Progress in Physical Geography, 23*(3), 329–357. **https://doi.org/10.1177/030913339902300302**

Winsemius, H. C., Schaefli, B., Montanari, A., and Savenije, H. H. G. (2009). On the calibration of hydrological models in ungauged basins: A framework for integrating hard and soft hydrological information. *Water Resources Research, 45*(12). **https://doi.org/10.1029/2009WR007706**

Yadav, M., Wagener, T., and Gupta, H. (2007). Regionalization of constraints on expected watershed response behavior for improved predictions in ungauged basins. *Advances in Water Resources, 30*(8), 1756–1774. **https://doi.org/10.1016/j.advwatres.2007.01.005**

Yang, Y., Pan, M., Beck, H. E., Fisher, C. K., Beighley, R. E., Kao, S. C., Hong, Y., and Wood, E. F. (2019). In Quest of Calibration Density and Consistency in Hydrologic Modeling: Distributed Parameter Calibration against Streamflow Characteristics. *Water Resources Research, 55*(9), 7784–7803. **https://doi.org/10.1029/2018WR024178**

Yapo, P. O., Gupta, H. V., and Sorooshian, S. (1998). Multi-objective global optimization for hydrologic models. *Journal of Hydrology, 204*(1–4), 83–97. **https://doi.org/http://dx.doi.org/10.1016/S0022-1694(97)00107-8**

Zeng, L., Xiong, L., Liu, D., Chen, J., and Kim, J. S. (2019). Improving parameter transferability of GR4J model under changing environments considering nonstationarity. *Water, 11*(10). **https://doi.org/10.3390/w11102029**

Zhang, Z., Wagener, T., Reed, P., and Bhushan, R. (2008). Reducing uncertainty in predictions in ungauged basins by combining hydrologic indices regionalization and multiobjective optimization. *Water Resources Research, 44*(12). **https://doi.org/10.1029/2008WR006833**

Appendix A – Glossary

Baseline	Data judged to best represent the past or current state of a system.
Baseline period	Time period for which baseline data are available. Similar, but not synonymous with the reference period.
Climate model	A numerical representation of a climate system based on the physical, chemical and biological properties of its components, their interaction and feedback processes, and accounting for all or some of its known properties. Regional climate models (RCMs) typically cover a region of the globe while global climate models (GCMs) cover the entire globe (adapted from Charron, 2016).
Climate products	Weather station data, observed gridded products, reanalysis, climatic simulations and climate scenarios.
Climatic simulation	Raw, downscaled and/or post-processed climate model simulations, as well as climatic simulations from weather generators.
Day-to-day behavior	Refers to the daily data, the sequences and the timing of events in observations or simulations. More specifically, climate models do not represent the day-to-day behavior of climate observations due to: the chaotic nature of the climate system, and their sensitivity to initial conditions. Climate models reproduce the statistical properties (mean, variance, inter-annual variability, etc.) of the observed records.
Data transformation method	Generic term used to represent any deliberate manipulation of a set of observed or simulated data, usually with the goal of increasing its plausibility and/or making it easier to work with. In the context of this Guidebook, these include delta, bias correction, reduction, adjustment and extension methods.
Driver	A cause of change.
Downscaling	A method that enables climate-model output data to be delivered over a finer resolution grid. The method can either be dynamical (e.g. RCMs) or statistical.
Emissions scenario	A plausible representation of the future development of emissions of substances that are potentially radiatively active in the atmosphere, such as greenhouse gases and aerosols. An emissions scenario is based on assumptions regarding drivers such as demographic and socioeconomic development, and technological change (adapted from Charron, 2016).
Energy model	A model used to simulate energy at a dam. The model considers inflows/reservoir levels, asset characteristics, operational management rules and constraints.
Ensemble approach	A way to account for uncertainties related to unknown future events and processes by integrating several options and combinations at each step of the modeling chain. For climate change studies, the ensemble approach typically includes simulations for various emissions scenarios, climate models, post-processing techniques, etc.
Global climate models	See climate models.
Gridded observations	Weather observations transposed on a grid using different techniques such as interpolation and kriging.
Hydrologic model	A simplification of a real-world system that aids in understanding, predicting, and managing water resources. In this Guidebook, a hydrologic model is typically used to simulate inflows to a reservoir or to a generating station. The model may include a routine for water routing. In most hydrologic models, reservoir operations are simple representations.
Internal variability	Variability obtained by a single GCM when it is run with slight perturbations in initial conditions or parameters. Internal variability is often used to approximate natural variability (see definition).
Modeling chain	A sequence of numerical models (e.g. climate models, hydrologic models, energy models and value models).
Natural variability	Fluctuations (in climate, in hydrology) that occur regardless of anthropogenic trends. This includes chaotic fluctuations as well as cycles on many timescales (e.g. multi-year, decadal and multi-decadal).

Naturalized	A term used to qualify hydrologic simulations that do not take into account water management decisions and/or regulated operations at upstream reservoirs and hydraulic structures.
Post-processed	Downscaled and/or bias-corrected climatic simulations.
Projection	A model's prediction of a future state based on assumptions, such as potential socio-economic and technological developments, that are subject to uncertainty (adapted from Charron, 2016).
Reanalysis	An estimate of historical atmospheric and oceanic temperatures, wind, current, and other meteorological and oceanographic quantities, created by processing past meteorological and oceanographic data using fixed state-of-the-art weather-forecasting models and data-assimilation techniques. Reanalyses facilitate the consideration of numerous climatic variables and are also used to validate RCMs and GCMs in the current climate, and to drive RCM simulations (adapted from Charron, 2016).
Reconstructed hydrology	Hydrologic simulation based on climatic baseline.
Regional climate models	See climate models.
Regulated	A term used to qualify a hydrologic baseline influenced by operations at upstream reservoirs and hydraulic structures. This term can also be used to qualify hydrologic simulations that take into account upstream reservoirs and hydraulic structures with water management models.
Reference period	A period of time from the recent past. Similar, but not synonymous with the baseline period
Scenario	A plausible, coherent and internally consistent description of a system. In the context of this Guidebook, a scenario represents the evolution in the climate, hydrology and/or energy for a given period, using a specific data transformation method, and under specific assumptions about the evolution of greenhouse-gas emissions and other factors that may influence future climate. Baselines and simulations integrating climate change serve as the raw material for constructing a scenario (adapted from Charron, 2016).
Simulation	The outcome of running a model for a certain period of time, ranging from a few years to millennia (in the past or future). A simulation can be run at various time intervals (minutes, hours, days, months, etc.) (adapted from Charron, 2016).
Simulation based on the baseline	Simulations made with a model or a series of models and that are fed by a baseline
Simulation integrating climate change	A simulation made with a model or a series of models that were initially fed by an emissions scenario and climatic simulations.
Water management model	A model that uses the inflow from the hydrologic model and includes a routine for water routing to move water between sub-catchments and through reservoirs, dams and hydraulic structures. It explicitly represents decisions related to storing and releasing water. Model options range from simple (defined rule curves) to advanced optimization routines that explicitly seek to maximize some criteria while respecting a series of constraints such as regulatory limits. A water management model is sometimes embedded in hydrologic models and energy models.
Weather Generator	A numerical model that produces synthetic climatic simulations based on the statistical characteristics of observed weather.

Appendix B – Detection and attribution in the context of climate change

The detection of a trend and its attribution to one or several causes is considered important at many points in this document. This Appendix summarizes some key general definitions and concepts associated with detection and attribution in the context of climate change. Most of what follows is extracted from reference documents and publications originating from both the field of climate science and of causal inference (Hegerl et al., 2007, 2010; IPCC, 2014; Pearl, 2009). They reflect the established principles on this topic.

B.1 Definitions of detection and attribution

The IPCC defines detection as the process of demonstrating that climate, or a system affected by climate, has changed in some defined statistical sense, without providing a reason for that change. For instance, under a statistical framework, an identified change is detected in observations if its likelihood of occurrence by chance alone is determined to be small (e.g. <10%).

The IPCC defines attribution as the process of evaluating the relative contributions of multiple causal factors to a change or event with an assignment of statistical confidence. More precisely, attribution seeks to determine whether a specified set of external forcings and/or drivers caused a detected change in the climate system, whether the change involves a climate variable (e.g. temperature, precipitation) or an impact-related variable (e.g. runoff, flooding, agricultural yields).

To evaluate the causal contribution of a given factor to a given change, the IPCC proposes a two-step test. Step one: the detected change must be consistent with combined estimated responses to anthropogenic and natural forcings. Step two: the detected change must be not consistent with alternative, physically plausible explanations that exclude important elements of anthropogenic forcings.

B.2 Need for detection and attribution of trends

Consider two examples that highlight the importance of detection and attribution studies. Note that these examples are for the prediction of high flows. Therefore, the methods used differ from the one suggested in this Guidebook. However, the same concepts apply to the valuation of assets. These examples highlight the need to develop a better understanding of not only a trend's cause, but also the role of each climatic and hydrologic driver before integrating climate change into the valuation of assets.

Luke et al., (2017) assessed different statistical distributions to predict flood frequencies. The cause(s) of the trend in flood frequencies was not identified prior to the exercise. The results (**Figure B1**) show that the extension of a trend can lead to poor results and that the use of a stationary statistical model, even if relevant in most cases, can also lead to poor results.

The second example, presented in **Figure B2**, is provided by François et al., (2019) and is of particular interest as it could be tempting to visually attribute the cause of the trend to climate change.

> "The Red River of the North at Fargo (North Dakota, U.S.) is a particularly salient example of non-stationary stream flow (**Figure B2**) (Mueller and Foley, 2014). Although flagged as regulated by the U.S. Geological Survey, the U.S. Army Corps of Engineers (USACE) demonstrated that changes in streamflow beginning in the early 1940's (Villarini et al., 2009a) cannot be explained by flow regulation (see discussion in Serinaldi and Kilsby, 2015); instead, tree-ring analysis has shown that the river experiences "high and low flood modes [...], which extend from several decades to nearly a century" (George and Nielsen, 2003)."

A)

B)

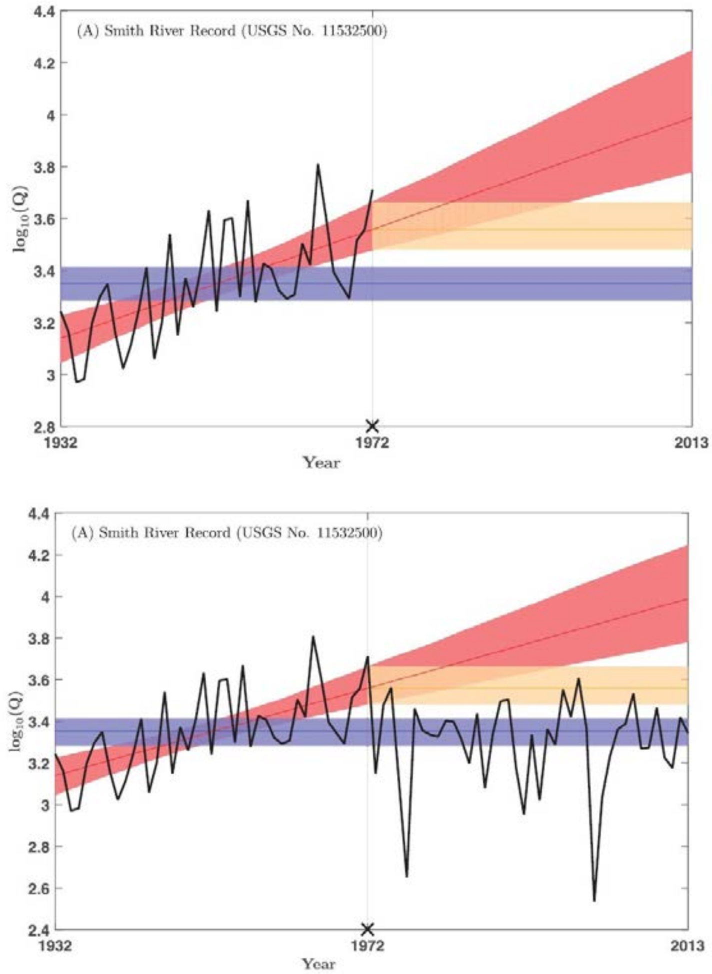


Figure B1 Example of results in the study by Luke et al., (2017). Panel A shows the first half of the streamflow record (black) on which the statistical distributions are fitted. It also shows two types of stationary statistical distribution and their confidence intervals (in yellow and in blue) and a non-stationary statistical distribution. Panel B shows the second half of the record to validate the statistical distributions. In this situation, the stationary statistical model in blue was the best choice to predict the future.

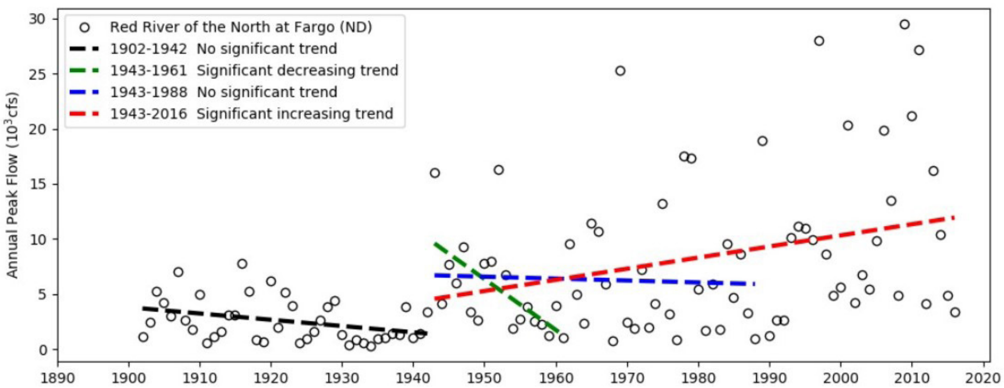


Figure B2 Annual peak flow for the Red River of the North at Fargo, North Dakota. Dashed curves show trends for various periods (François et al., 2019)

B.3 Articulation with causal theory: necessary and sufficient causation

It is of interest to emphasize the consistency of the above two-step test in the more general context of causal theory.

David Hume, 18th Century Scottish philosopher, defined causality as: "an object followed by another, where, if the first object had not been, the second never had existed." In other words, an event E is caused by an event C if and only if E would not have occurred were it not for C. According to this definition, causality requires a counterfactual approach in which event C is removed, and the plausibility of event E is assessed. The fundamental concept of causality implied by Hume's qualitative definition is still relevant in the standard causal theory (e.g. Pearl causal theory) used nowadays. The standard causal theory states that two distinct facets of causality should be distinguished: necessary causation, where the occurrence of E requires that of C but may also require other factors; and sufficient causation, where the occurrence of C drives that of E but may not be required for E to occur.

These concepts of causal theory provide a better understanding of the two-step attribution definition given by the IPCC: consistency with the estimated responses to combined anthropogenic and natural forcings correspond to sufficient causation; and inconsistency with alternative, physically plausible explanations that exclude anthropogenic forcing corresponds to necessary causation.

B.4 Importance of mechanistic understanding

The necessary and sufficient causation rely on what is often referred to as a difference-making concept of causality, one based on experimentation and on testing the influence of a given factor on a given outcome. This approach is often considered insufficient: while it may provide convincing evidence of the existence of a causal link, it does not provide any understanding of this causal link. Understanding usually relates to accessing the knowledge and description of the mechanisms underlying the causal link.

One can therefore consider mechanistic understanding as a third, qualitatively distinct, condition deemed necessary to prove causality, with the other two being the necessary and sufficient causation described previously.

While there are differences between the mechanistic and difference-making concepts of causality, there are also close connections: on the one hand, our knowledge of underlying mechanisms guides our causal assumptions; while on the other, evidence of causal relationships helps us discover mechanisms.

B.5 Single step versus two steps

Attribution in the context of climate change establishes a methodological distinction between single-step and two-step attribution. Note that the distinction is merely methodological; the underlying causal definition is the same.

For example, increased greenhouse gas concentrations may be a driver of an observed change in the climate system. In turn, changed climate may be an external driver of impact-related aspects such as crop yields or glacier mass.

Single-step attribution to external forcings comprises assessments that attribute an observed change within a system to an external forcing based on explicitly modeling the response of the variable to external forcings and drivers. Modeling can involve a single comprehensive model or a sequence of models. The attribution step involves detection of a significant change in the variable of interest and comparison of observed changes in the variable of interest with expected changes due to external forcings and drivers (typically derived from modeling approaches).

Two-step attribution to external forcings comprises assessments that attribute an observed change in a variable of interest to a change in climate and/or environmental conditions, plus separate assessments that attribute the change in climate and/or environmental conditions to external drivers and external forcings. An example would be the multistep attribution of declining marine calcification to rising levels of atmospheric carbon dioxide (i.e. changes in marine calcification are attributed to changes in ocean chemistry, which in a separate step is attributed to changes in atmospheric carbon dioxide). In the case of climate extremes and rare events, for example, it may not always be possible to reliably estimate from observations whether there has been a change in frequency or intensity of a given type of event. Nevertheless, it may still be possible to make a multistep attribution assessment of an indirectly estimated change in the likelihood of such an event, if there is a detectable change in climatic conditions that are tightly linked to the probability of that event (for example, a change in the frequency of rare heat waves may not be detectable, while a detectable change in mean temperatures would lead to an expectation of a change in heat-wave frequency). This method involves a sequence of analyses, including synthesis of observational data and model applications. The assessment of the link between climate and the variable of interest may involve a process model or statistical link, for example, or another downscaling tool. It is recommended that the component assessments (or steps) be made explicitly (each with its own level of confidence), along with an overall assessment of the combined result. The overall assessment will generally be similar to or weaker than the weakest step.

B.6 Examples

To summarize, there are three components to causal attribution:

- counterfactual inconsistency
- factual consistency
- mechanistic understanding

For instance, let us revisit the arguments supporting the attribution of climate change to human activities. Note that in this example, the counterfactual inconsistency can be verified with counterfactual simulations (natural forcings only) available in the CMIP ensembles.

- Counterfactual inconsistency: Historical estimates of past climate changes suggest that the recent changes in global surface temperature are unusual. Computer-based climate models are unable to replicate the observed warming under natural forcings only. In other words, natural forces alone (such as solar and volcanic activity, as well as internal climate variability) cannot explain the observed warming.
- Factual consistency: Historical estimates of past climate changes are consistent with anthropogenic emissions. Computer-based climate models always replicate the observed warming when forcings include human greenhouse gas emissions.
- Mechanistic understanding: A physical understanding of the climate system is available (i.e. the warming properties of greenhouse gases are well understood and established).

Here is an example that would support the attribution of a change in streamflow to land use changes:

- Counterfactual inconsistency: A recently calibrated hydrologic model is unable to reproduce an unusual change in streamflow observed in the historic data under the assumption of stationary parameters. In other words, forcing a static watershed model with precipitation and temperature does not reproduce the observed change in streamflow.
- Factual consistency: Historical records of changes in streamflow are consistent with aerial imagery of forest loss (e.g. due to fire or logging activity). The hydrologic model that accounts for land-use change in line with historic imagery or logging records, etc. does replicate the observed change in streamflow.
- Mechanistic understanding: A physical understanding of the watershed indicates that the removal of surface vegetation increases its mean annual streamflow (i.e. rainfall produces more runoff).

This trend may be justifiably included in a model of future conditions, particularly if it aligns with a forest management plan that has future planning conditions or rules available.

Appendix C – GCM selection methods

As explained in **Section 2.3** – Sources of uncertainty, the ensemble approach is used to characterize the uncertainty of future emissions scenarios and climate models. As the number of models rises quickly and can become challenging on the computational side, GCM selection methods, presented in this Appendix, are emerging. The goal of these methods is to select a subset of GCMs that adequately represent most of the full ensemble and its uncertainty.

Selection methods for GCM ensembles range from removing a few models with large biases (outliers) to using an optimal combination of models; however, all methods require time and resources. Therefore, **Appendix C** is most relevant for those with the time and resources needed to conduct more advanced analyses.

It is noted that while this discussion focuses on GCMs, some of its selection concepts also apply to RCPs and other models (RCM, hydrologic models).

C.1 Driving needs for selection

The optimal selection of GCMs depends on the needs of the assessment. Some assessments require best – and worst-case scenarios. Other assessments may require a smaller range of projections and focus on a central tendency. The assessment may also have practical constraints, such as limited processing time.

C.2 GCM ensembles – key concepts

The following key concepts underlie the principles of ensemble selection.

- There are many GCMs. There is an ever-increasing number of climate change models. For example, the next CMIP generation is estimated to be 10 times larger than the existing generation (Eyring et al., 2016).
- Some models are outliers. When projecting hydrologic changes, some individual climate models may stand out from the ensemble (due to overestimation or underestimation biases) and carry a large fraction of the climate projection uncertainty (Gao et al., 2019; Her et al., 2019; Hosseinzadehtalaei et al., 2017).
- Some models are similar. It is common for GCMs within an ensemble to share components (Knutti et al., 2013; Sanderson et al., 2015). Similarity among GCMs can result in similar future projections and users should be aware of this feature when selecting an ensemble that sufficiently represents uncertainty and when interpreting ensemble statistics.

- Some GCMs better represent observed climate. Models differ in their ability to represent the observed climate (IPCC 2013) and hydrologic processes when coupled with hydrologic models (Ignazio Giuntoli et al., 2018).
- GCMs that better represent observed climate will not necessarily perform better in the future. Better ability to represent the observed climate does not guarantee the validity of future projections (Hosseinzadehtalaei et al., 2017; Klein and Hall, 2015).
- Accuracy depends on variable, geography and timescale. No model has been shown to outperform all others across multiple diagnostics, indices or timescales (Charron, 2016; Wang et al., 2018; Wilby, 2010). For instance, models that perform well historically for temperature (important for snow processes) may be less reliable for precipitation.
- The coverage of impact model variables differs from that of climate variables. Even though a subset of GCMs may cover most of the uncertainty associated with climate variables (e.g. precipitation), the same coverage is not guaranteed to extend to hydrologic impact variables, because the transfer process from climate to hydrology is complex and non-linear (Chen et al., 2016; Wang et al., 2018).

C.3 Driving need #1: Maximizing uncertainty

In some instances, the practitioner may need to know the best – and worst-case scenarios for sensitivity testing, for instance, or to prepare for the most extreme consequences. These scenarios can be obtained by maximizing the model diversity (i.e. by obtaining models with different characteristics) at each step of the modeling chain (Hosseinzadehtalaei et al., 2017; Schaefli, 2015). The selection of a subset of GCMs representing the best – and worst-case scenarios should therefore be accomplished as late as possible in the modeling chain.

Selection option

- Envelope method – One approach to selecting a subset of models is to retain the best – and worst-case scenarios, based on the goal of adequately representing the full range of possible future conditions for the indices of interest (Charron, 2016; Wang et al., 2018).

With this approach, there is greater confidence that the range of models obtained will encompass the future trajectory. However, the assessment should not be unrealistically confident, as even the inclusion of all available models does not guarantee that all possible future hydrologic projections are covered (Wang et al., 2018).

C.4 Driving need #2: Optimizing uncertainty

The Maximizing uncertainty approach may not always be appropriate for decision-making. Consider, for instance, that the approach results in a range of climate projections representing drastically different hydrologic impacts (e.g. different directions of change). Decision-makers may need a smaller range of results that still capture most of the projection uncertainty. As a result, practitioners need a method to optimize their understanding of uncertainty.

Selection options

- Past performance methods – These methods select a subset of GCMs (or alternatively, weigh models differently) based on their ability to represent the observed climate (Wang et al., 2018). For example, models may be included or excluded on the basis of credibility in medium/low flow representation (Ignazio Giuntoli et al., 2018). The challenge is that a climate model that generates relatively accurate present-day simulations will not necessarily generate accurate long-term projections (Hosseinzadehtalaei et al., 2017), although it may be possible to focus on processes that dictate long-term climate evolution (Klein and Hall, 2015). Some studies have proposed selection methods that combine both recent-past performance and climate change envelope coverage criteria (Wang et al., 2018).
- Removing outlier projections – A handful of studies have investigated how uncertainty varies based on individual climate models (Gao et al., 2019; Her et al., 2019; Hosseinzadehtalaei et al., 2017). This type of analysis can help identify which models most contribute to the uncertainty of an ensemble. These unrealistic (most different) models can be removed when trying to reduce uncertainty contained in the subset of GCMs (Maraun and Widmann, 2018).

C.5 Driving need #3: Practical constraints

Another potential reason to select a subset of GCMs is the need to increase efficiency in the modeling chain due to practical constraints, such as time and budget. Although it is usually advised to use as many (credible) climate models as possible in impact studies, the extraction, storage and computational costs associated with large ensembles may be prohibitive (Chen et al., 2016; Wang et al., 2018). In practice, it is not uncommon for impact studies to rely on a subset of climate models due to feasibility (Charron, 2016; Wang et al., 2018). The selection purpose in this case is to have a smaller number of models.

Whenever possible, this selection should be based on climate indices that represent the primary drivers of the impact model (hydrology, energy production, and/or asset value), rather than on indices such as mean annual precipitation or temperature (Chen et al., 2017; Seo et al., 2019). In the case of high flows, for example, such an index could be the maximum 72h precipitation. Finding these representative indices could require extensive analyses of past data, but maximizes the possibility of having an adequate climate model ensemble.

Selection options:

- Any of the methods previously described (envelope, past performance, removing outliers)
- Grouping/clustering methods – Another approach to selecting a subset of GCMs is to minimize repetition among similar models by grouping them and taking a representative model from each group. This is done by calculating the differences between all models with respect to the variables of interest (Casajus et al., 2016; Sanderson et al., 2015; Wang et al., 2018)

Appendix D – Transferability of data and results

Practitioners may need to transfer information from one situation to another, or one project to another. Because climate change impact assessments are performed as a modeling chain, there may be transferability of information at different steps of the chain, i.e. transferability of climatic information (e.g. climate data, climate projections) and hydrologic information (e.g. present-day flows, future hydrology projections). For example, practitioners may need to know whether the findings of studies conducted on another geographic area can be applied to their watershed (transferability between watersheds). Alternatively, practitioners may rely on outputs from global impact models, and ask themselves whether results can be transferred from the scale of the impact model (transferability between spatial resolutions). Lastly, practitioners conducting their own analyses may need to know whether a model calibrated during wet years performs correctly during years of drought (transferability between time periods).

Ultimately, practitioners need to use the best available information and to critically compare how different data or findings may or may not be transferable to a particular watershed. Practitioners must recognize the potential limitations of transferring information. Appendix D explores the relevant factors to consider.

D.1 Transferability between watersheds

D.1.1 What is the challenge?

Practitioners may need or may want to transfer information from one watershed to another. Although many climate change impact studies are based on watershed-scale projections (Schaefli, 2015), these studies may not be relevant to the study of another region. The shortage of reliable hydrologic data is a worldwide issue due to the costs and logistics associated with monitoring networks. Therefore, most watersheds in all climatic regions remain ungauged (Maréchal and Holman, 2004). Even in gauged watersheds, it is necessary to make forecasts not only at the watershed outlet but also at certain places within the watershed (Hunukumbura et al., 2012).

However, transferring climactic or hydrologic findings/projections from one area to another is a challenge because models have parameters that are calibrated based on unique climatic and physiographic factors (Schaefli, 2015). Even within small regions, the interdependence of climate, hydrology and hydropower production may vary strongly (Schaefli, 2015; Wilby, 2010). For example, the relationship between temperature increase and hydrologic cycle can differ significantly from one region to another (Hattermann et al., 2018; Schaefli, 2015). In some regions, increases in temperature and radiation may stimulate evapotranspiration and reduce water availability, while in other regions these may stimulate precipitation rather than evapotranspiration and increase water availability (Hattermann et al., 2018). Opposing trends can develop even within a single watershed (Hattermann et al., 2018). Even after calibrating a hydrologic model at a watershed outlet, the model parameters may not be transferable to internal ungauged sub-watersheds (Hunukumbura et al., 2012).

D.1.2 Factors to consider

Before transferring information from one watershed to another, it is important to consider the similarity of the watersheds' climactic and hydrologic processes. The factors below can be used as a guide (Kour et al., 2016, Schaefli 2015, Hattermann et al., 2018, Hunukumbura et al., 2012), as well a consideration of the degree of flexibility of the method/model.

How similar is the physiography and climate?

- Latitude and spatial proximity
- Altitude and topography
- Proximity to water bodies
- Climate seasonality
- Precipitation type (e.g. snow)

How similar are watershed characteristics and processes?

- Watershed size
- Topography (e.g. slope)
- Geology
- Land use/urbanization
- Ecozone/vegetation
- Natural and artificial water storage
- Role of groundwater
- Seasonal water-balance behaviour
- Presence of glaciers or snowpack
- Watershed heterogeneity

TRADING SPACE FOR TIME IN CLIMATE CHANGE IMPACT STUDIES

A parallel can be made between the transfer of time parameters and the transfer of space parameters (Coron et al., 2012). This is increasing popular for assessing the hydrologic implications of anthropogenic climate change (Patil and Stieglitz, 2015). For example, Singh et al., (2011) evaluated the ability to extrapolate parameters (for climate change) by transferring them to other catchments in warmer climatic zones (Coron et al., 2012). Merz et al., (2011) found that variations of parameters over time and space were comparable. Patil and Stieglitz (2015) suggests that further exploration is therefore needed on how to compare spatial and temporal parameter-transfer approaches.

D.2 Transferability between spatial resolutions

D.2.1 What is the challenge?

Practitioners need to transfer information from one spatial resolution to another. Climate change impact assessments are often implemented in regional contexts, while most hydrologic analyses consider larger spatial extents. (Her et al., 2019).

However, transferring climactic or hydrologic findings/projections from one spatial resolution to another is a challenge because large-scale analyses do not consider detailed processes, and localized impacts may not be efficiently represented (Her et al., 2019). The original intent of GCMs was to assess global change; it is only more recently that they have been used to inform adaptation measures at regional and local scales (Wilby, 2010).

For example, hillslope processes (e.g. infiltration, overland flow) are more dominant in small watersheds, while channel routing and groundwater flow may control the overall hydrology of large watersheds (Her et al., 2019). In addition, homogeneity can be reasonably assumed for a hillslope, whereas a large watershed usually has considerable heterogeneity (Her et al., 2019). The hydrologic responses from areas of large watersheds are likely to be mixed and dampened through prolonged overland and channel processes (Her et al., 2019).

D.2.2 Factors to consider

Before transferring information from one spatial scale to another, it is important to consider differences in climactic and hydrologic processes. The factors below can be used as examples (Her et al., 2019; Wilby, 2010).

- What are the dominant processes?
- Dominant hydrologic processes (e.g. hillslope vs. channel routing)
- How scale compares to that of atmospheric processes (e.g. thunderstorms)
- Watershed homogeneity
- Time of response (e.g. influence of groundwater)

It is noted that there exist some empirical transfer functions (by assuming scale-independent distribution functions with regionalized distribution parameters) to transfer global parameters to regional scales; however, these have yielded mixed results (Samaniego et al., 2010, 2017).

D.3 Transferability between time periods

D.3.1 What is the challenge?

Practitioners may need to transfer information from one time period to another. This is a critical issue in the context of climate change impact studies, because climate and hydrologic models are developed for observed conditions and then applied to future conditions (Coron et al., 2012; Schaefli, 2015). Fluctuations in historical climate can also be an issue if flows are simulated for a period that is different than the one used in the calibration (Coron et al., 2012). Other situations where the model is calibrated in one period and then extrapolated to another include forecasting, design and reservoir management (Coron et al., 2012; Maréchal and Holman, 2004).

However, transferring climactic or hydrologic findings/projections from one time period to another is a challenge because optimal model parameters vary with time. As reported by Coron et al., (2012), many authors have observed decreases in model performance (i.e. larger model errors) after transferring parameter sets between climatically contrasted periods. For example, parameter values can vary seasonally because of differences in dominant hydrologic processes controlling runoff generation in different seasons (Coron et al., 2012). Hence, calibration over a wetter (drier) climate than the validation climate leads to an overestimation (underestimation) of the mean simulated runoff (Coron et al., 2012; Motavita et al., 2019). The risk of poorly transferring information across time periods is that the results may inspire overconfidence (Motavita et al., 2019).

Parameter dependency on climate has been investigated using the differential split-sample test (SST), where calibration and validation periods are chosen according to their climatic differences (Coron et al., 2012). Coron et al., (2012) reports a lack of consensus in the literature on the success of parameter transfer between different time periods, and postulates that the results vary from watershed to watershed.

D.3.2 Factors to consider

Before transferring information from one time period to another, it is important to consider the similarity between the two periods. The factors below can be used as a guide (Coron et al., 2012; Motavita et al., 2019).

How was the model calibrated?

- Length of record
- Availability and quality of data (e.g. missing data)
- Diversity of climactic and hydrologic conditions

How similar are the two periods?

- Climatic conditions
- Dominant hydrologic processes (e.g. seasonal modification of groundwater balance)
- Watershed characteristics (e.g. seasonal modification of vegetation)

D.4 Transferability between time resolutions

Hydrologists have widely studied the time dependence of hydrologic models (Jie et al., 2018; Reynolds et al., 2017). The temporal resolution of observed data has been found to be a critical element in determining the parameters, prediction performance and applicability of hydrologic models (Jie et al., 2018). In many areas, hydrologic observation data are available only for longer time periods (e.g. daily), whereas model applications may require finer temporal resolutions (e.g. 6-hour; Jie et al., 2018). Practitioners are advised to search for climatic and hydrologic information that is of similar temporal resolution to their application.

Appendix E – Validation of climate products

This appendix provides the practitioner with a comprehensive approach to evaluating the adequacy of climate products (weather station data, observed gridded products, reanalysis, climatic simulations and climate scenarios) and to determining whether a climate product suits the valuation modelling chain.

Section E.1 presents general concepts and specific examples of the approach, **Section E.2** considers relevant limitations, **Section E.3** examines the approach more closely and **Section E.4** considers several examples.

E.1 General concepts

The approach is based on the idea that for a climate product to be adequate for hydrologic modeling, it must meet certain requirements when it is compared to a given baseline or reference. The approach should be applied to any climate product prior to its use in a hydrologic model. Indeed, hydrologic models for the modeling chain need to be calibrated on observed streamflow and therefore need a good quality input to produce an acceptable output. Furthermore, understanding the strengths and limitations of the climate product will help with the interpretation of the hydrologic simulation results (Krysanova et al., 2018). The procedure is typically referred to as an evaluation diagnostic (Maraun and Widmann, 2018).

Maraun and Widmann (2018) describe the regional climate by analyzing marginal, temporal, spatial and multivariate aspects, as well as seasonal and spatial variations. In this regard, the approach relies on a multitude of indices to characterize the complexity of the climate. To evaluate its performance, the climate product is compared to a fixed baseline with regard to the climate indices. Variables used as input to a hydrologic model – typically minimum and maximum temperatures as well as precipitation – thus need to be validated with the approach.

This comprehensive approach is well suited to business decisions that necessitate a lot of attention to detail. Based on the practitioner's expertise, parts of the approach may also be used to inform other business decisions.

Specific uses of the approach include the evaluation and comparison of the performance of:

1) Gridded observations and reanalysis datasets versus observations
2) Multiple post-processed climate model simulations
3) Multiple weather generators

This approach should not be used to evaluate and compare the performance of raw climatic simulations. Refer to Maraun and Widmann (2018) for such an exercise.

E.2 Limitations

Limitations of the suggested validation are listed below.

- Validation of climate products might not be sufficient to evaluate suitability for the valuation modeling chain. The hydrologic validation of **Appendix G** – Validation of hydrologic simulations might also be necessary (see example in Chen et al., (2019)).
- The threshold for the adoption/rejection of a climate product is left to the practitioner's judgement. See Maraun and Widmann (2018) for further information on the relevance of significance tests.
- The approach is restricted to a climatic validation, or more specifically to climate products expected to climatologically represent the climatic baseline and not day-to-day behavior (see the Glossary for more information on day-to-day behaviour).
- The approach is limited by the availability of a climatic baseline for the region of interest.
- The approach is also limited by the quality and the reliability of the climatic baseline. As discussed in **Section 4.1** – Climatic baseline, the baseline is most surely subject to certain errors and sources of uncertainty.
- For specific use 1) Gridded observations and reanalysis datasets versus observations, the approach is limited by the existence of independent weather stations (i.e. some that were not used to produce the gridded observations or the reanalysis).

E.3 Methods

E.3.1 Defining baseline, spatial scale and period

The first step is to identify a proper baseline for the validation. The proper baseline for specific uses 2) Multiple post-processed climate model simulations and 3) Multiple weather generator, is the baseline identified in **Section 4.1** – Climatic baseline. A proper baseline for specific use 1) is independent weather stations (i.e. weather stations not used to produce the gridded observations or the reanalysis). However, independent weather stations do not always exist or are not always available and therefore, validation of the climate product cannot be carried out.

The practitioner also needs to decide on spatial scale: at the weather stations, grid points or watershed. This decision can depend on whether the hydrologic model is lumped or distributed and may be constrained by data availability.

The same time period (concomitant years) in the baseline and the climate product should be used while carrying out the validation to avoid inconsistencies due to low natural variability cycles and to climate change signal.

E.3.2 Validating the climate products

As mentioned in **Section E.1**, the validation compares the characteristics (indices, indicators) of certain variables obtained from a climate product to those obtained from a reference dataset (i.e. the baseline). These characteristics rely on key statistical properties of the variables of interest, and the aim is to verify that the climate product reproduces adequately the statistics of the baseline dataset for the indices deemed important by the practitioner. General statistics, such as annual averages and inter-annual variability about these averages, need to be checked to ensure that the general behavior of the variables of a climate product is similar to that of the baseline. Other general indices are the average yearly profiles (or cycles) of variables at a given temporal scale (daily, weekly, monthly, etc.) of interest; for example the time scale of the hydrologic model used is of particular interest. Furthermore, the variability of the cycles throughout the years of the studied period is also important to analyze. **Section E.3.3** lists more specific indices for hydrologic modelling.

To validate the climate product, follow the three steps outlined below: general validation; validation of all indices considered; and in-depth analysis. If the simulated dataset does not perform adequately for a given climate index, it indicates a limitation of the dataset and the dataset should not be used to predict the future of this climate property.

1. General validation

General validation applies to all climate variables of interest, usually minimum and maximum temperatures, and precipitation for hydrologic modelling. For a given variable X, Xobs represents the baseline values and Xsim represents the climate product values. For general validation, **Table E1** presents the main quantities of interest.

Table E1 Quantities of interest denomination and examples for the general validation

Quantities of interest	Denomination	Example for a 30-year baseline
Annual averages (AA)	AA-Xobs, AA-Xsim	Annual average of the 30 years (30 values) of Xobs & Xsim
Averages over the years for a specified temporal scale (T) – usually a day, week or month (TA)	TA-Xobs, TA-Xsim	T=month; monthly averages of the 360 months (30 years x 12 months = 360 values) of Xobs and Xsim
Min. and max. of Xobs and Xsim (Tmin and Tmax) with time step T	TMin-Xobs, TMin-Xsim, TMax-Xobs, TMax-Xsim	T= month; minimum and maximum of Xobs and Xsim during a month, for every 360 months (30 years x 12 months = 360 values)

1.1. Compare mean of annual averages AA-Xobs and AA-Xsim for the presence of bias.

1.2. Compare standard deviation of AA-Xobs and standard deviation AA-Xsim for the presence of bias in inter-annual variability.

1.3. Plot time series

- Plot Xobs & Xsim as a function of time.
  - Are there any problems with the data?

1.4. Plot annual time series

- Plot AA-Xobs and AA-Xsim as a function of time. See **Figure E1** for an example.
- For specific use (1):
  - Are there trends in AA-Xobs and AA-Xsim? If so, do they correspond to one other?
  - If there is a trend in either AA-Xobs or AA-Xsim, its possible causes need to be studied. See **Appendix B** – Detection and attribution in the context of climate change.
  - If the trends in AA-Xobs and AA-Xsim do not correspond to one other and the difference cannot be explained by their causes, further investigation is needed.
- For specific use (2):
  - Are there trends in AA-Xobs? What are their causes?
  - Because of natural variability, trends in AA-Xsim must be evaluated using the ensemble approach (Maraun and Widmann, 2018).

- For specific use (3):
  - Are there trends in AA-Xobs? What are their causes?
  - If only one generated dataset is available, trends in AA-Xsim can be studied as with specific use (1). If several generated datasets are available, an ensemble approach (specific case (2)) may be used. The ensemble approach will minimize the effects of stochastic variability for trend analysis.

1.5. Plot annual cycles (mean-climatology).

- Plot mean, minima and maxima of TA-Xobs & TA-Xsim throughout T (see **Figure E2** for an example with T = one month).
- Is the cycle well represented by the simulation?
- Is the variability of the cycle well represented?

1.6. Plot annual cycles (min and max).

- Plot TMin-Xobs & TMin-Xsim throughout T (similar to graphic at point 1.5).
- Plot TMax-Xobs & TMax-Xsim throughout T (similar to graphic at point 1.5).
  - Is the variability of the cycle well represented?

1.7. Plot spatial patterns of daily values.

- Plot maps of daily values for the region of interest. If working with gridded datasets, it is worth doing these graphs before aggregation at the weather station or watershed scale.
- Plot maps of min-Xobs and max-Xobs, and min-Xsim and max-Xsim. Plot maps of Xobs and Xsim for any other day.
- Are there any spatial patterns that do not look like weather patterns? See **Figure E3**.

1.8. Plot annual average over time.

2. **Validation of simulations for all climate indices of interest**

In this step, all indices judged relevant by the practitioner are studied. **Section E.3.3** gives a list of climate indices useful for hydrologic modelling.

The analyses of step 2, although conducted in a fashion similar to those in step 1, go further by looking at more detailed climate properties as measured by a larger scope of climate indices.

The following is an example for proportion of wet days at the monthly time step (T=M) that should be replicated for all relevant indices.

Table E2 Quantities of interest denomination and examples for the validation of simulations for all climate indices of interest

Quantities of interest	Denomination	Example for a 30-years baseline
Proportion of wet days over the months	MwetD-Xobs, MwetD-Xsim	T=month, proportion of wet days for the 360 months (30 years x 12 months = 360 values) of Xobs & Xsim

2.1. Compare mean of annual averages MwetD-Xobs and MwetD-Xsim for the presence of bias.

2.2. Compare standard deviation of MwetD-Xobs and standard deviation MwetD-Xsim for the presence of bias in inter-annual variability.

2.3. Plot annual time series.

- Plot MwetD-Xobs & MwetD-Xsim throughout the years of the period (12 months=12 graphics).

2.4. Plot annual cycle.

- Plot mean, minimum and maximum of MwetD-Xobs & MwetD-Xsim throughout T.

2.5. Plot any other types of relevant graphic for the quantities.

The results can be plotted on a graph and/or compiled using heatmaps (see **Figure E4**) and performance metrics such as the mean squared skill score, the reduction of variance skill score or the Kuiper goodness-of-fit metric (Diaconescu et al., 2018).

If the simulated dataset does not perform adequately for a climate index, it indicates a limitation of the dataset. It should be used with caution if the climate index is of particular importance in the modeling chain.

3. Carry out in-depth analysis for specific uses 2) and 3).

This step takes into consideration structural elements of the climate models used to obtain the climate products. Maraun and Widmann (2018) suggest and explain several in-depth analyses related to topics such as the added value of RCMs.

E.3.3 Defining climate indices

Maraun and Widmann (2018) specify that: "indices need to be user specific and well selected to derive relevant information for a given context" and provide few starting points to build a list. In the context of the valuation of assets, this list can change according to type of asset (reservoir/runoff-river), watershed size, type of hydrologic model, types of revenues (energy, power and ancillary services), etc.

The list below presents climate indices that are of interest generally for hydrologic modelling (Fournier et al., 2015; Fournier and Merleau, 2016) as another starting point. Practitioners can also use the climatic baseline and sensitivity analysis presented in **Appendix H** – Sensitivity Analysis to identify their own indices or to prioritize the ones from the list below.

Precipitation

- Precipitation intensity: daily, monthly, seasonally and annually. For monthly, seasonal and annual processing, averages and accumulations are relevant. For seasonal and annual quantities, average over years.
- Proportion of dry and wet days: daily, monthly, seasonally and annually. For seasonal and annual quantities, proportion over years.
- Sequence of dry and wet days per month, season and year. For seasonal and annual quantities, proportion over years.
- Annual profiles at the daily time step of transition probabilities between dry (d) and wet (w) days, with different lags.
  - One-day lag: d | d; d | w; w | d; w | w (for example, d | w: dry day given the previous day is wet)
  - Two-day lag: d | d, d; d | d, w; etc.
  - Three-day lag: d | d, d, d; d | d, d, w; etc.

Temperatures

- Minimum temperature (Tmin) and maximum temperature (Tmax) as well as the average of Tmin and Tmax (Tmean) and daily thermal amplitude (DTA = Tmax-Tmin).

    - Without conditioning on the presence of precipitation
        - Distributions (e.g. boxplot): monthly, seasonal and annual
        - Daily profiles for average and standard deviation
        - Average and standard deviation over time: seasonal and annual
    - Conditioning on the presence of precipitation (d or w)
        - Distributions (e.g. boxplot): monthly, seasonal and annual
        - Daily profiles for average and standard deviation
        - Average and standard deviation over time: seasonal and annual
- According to Tmin
    - Number of freezing days: Monthly, seasonal and annual over years
    - Number of cold waves (spells) over years
- According to Tmax
    - Number of heat waves over years

Temporal dependencies of the variables and between variables at the daily time step

Correlations are used to study the different dependencies, once the data at a given time step have been standardized (centered and scaled) according to the two following conditioning approaches.

- Without conditioning on the presence of precipitation
    - Temporal:
        - Corr [X(t-h), X(t)] for X = Tmin, Tmax, Tmean & DTA; h = 1, 2, ...
    - Between variables:
        - Corr [X(t), Y(t)] for X = Tmin, Y = Tmax and X = Tmean, Y = DTA
- Conditioning on the presence of precipitation (d or w), with daily standardized variables
    - Temporal:
        - Corr [X(t-h), X(t)] for X = Tmin, Tmax, Tmean & DTA; h = 1, 2, ...
    - Between variables:
        - Corr [X(t), Y(t)] for X = Tmin, Y = Tmax and X = Tmean, Y = DTA
        - For wet days only, corr [X(t), Y(t)] for X = Tmin, Tmax, Tmean and DTA; and Y = Precipitation intensity (P) and log(P).

Dependence of variables on different watersheds

Correlation of variables as in the previous section between different watersheds/grid points

E.4 Examples

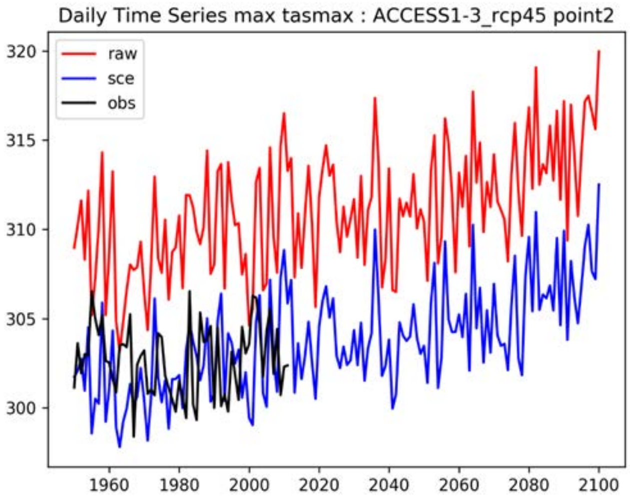


Figure E1 Example of annual profile for AA-Xobs and AA-Xsim as a function of time. AA-Xsim was computed on a post-processed climate simulation. The red line (raw) represents AA-Xsim computed on the raw climate simulation.

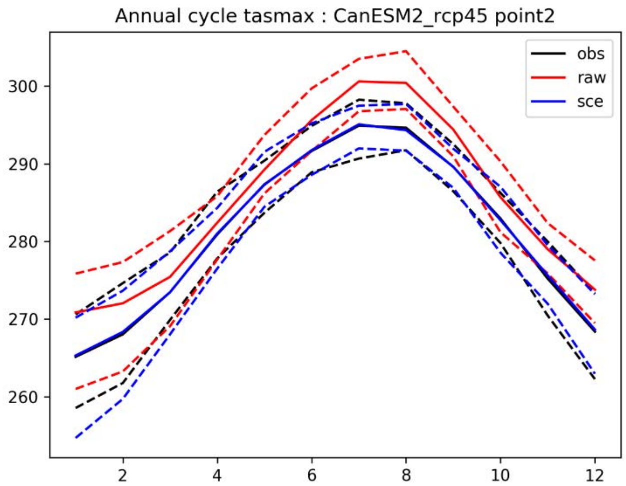


Figure E2 Example of annual profile for mean (climatology) TA-Xobs and for mean TA-Xsim. TA-Xsim was computed on a post-processed climate simulation. The red line (raw) represents TA-Xsim computed on the raw climate simulation. Dotted lines represent the min and max.

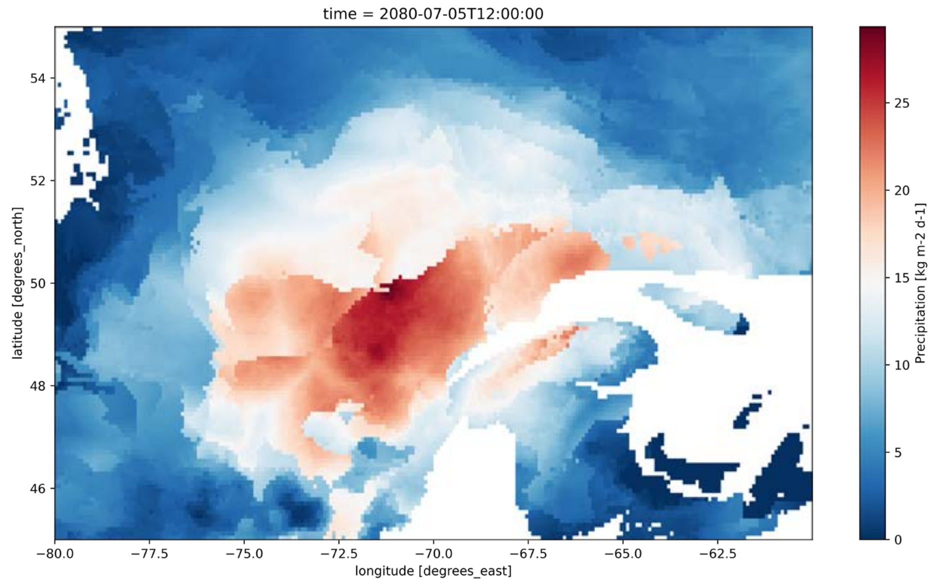


Figure E3 Example of daily precipitation map showing patterns not corresponding to typical weather patterns. The data come from a post-processed GCM simulation. Note that not all post-processing techniques provide similar results.

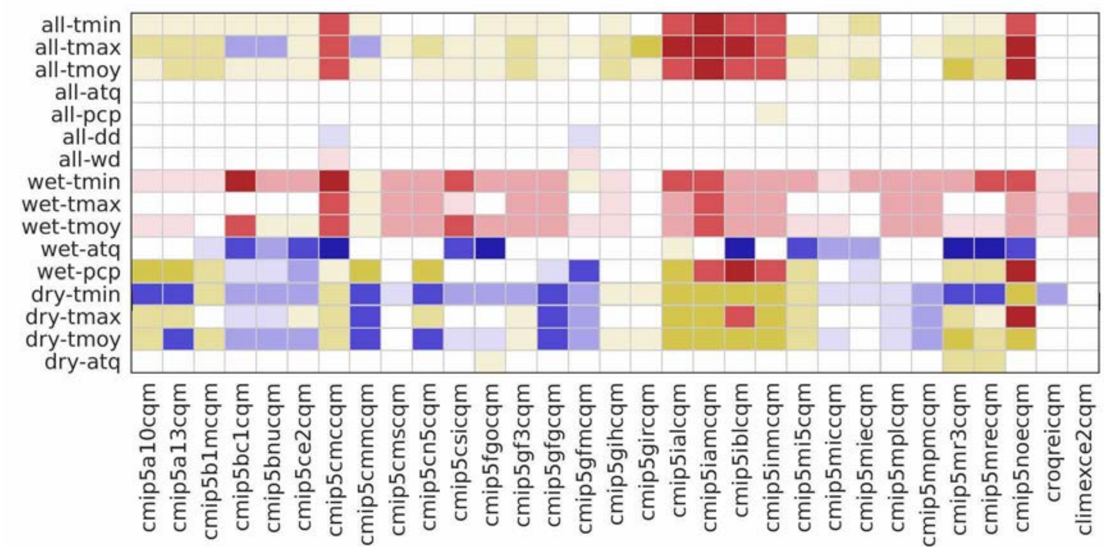


Figure E4 Example of heatmap for several climate indices (left) and several GCMs and RCMs simulations (bottom). Colour and hue illustrate performance. Each square represents the performance for several sub-watersheds. Blue is for an underestimation of the median performance, red for an overestimation and yellow for an accurate estimation. The darker hue means that less of 25% of the simulations agree with the observation, while the lighter hue means that more than 75% of the simulations agree with the observation. Agreement is determined by the overlap of quantiles between the observations and the simulations (Fournier and Merleau, 2016).

Appendix F – Selection and calibration of a hydrologic model

This Appendix aims to review the considerations needed to properly choose and calibrate a hydrologic model for a climate change study. Aspects to consider include: the hydrologic model itself (lumped versus distributed, conceptual versus physical); the number of parameters and their interaction; the chosen calibration period; and the quantity and quality of input data. The methodology to be used to choose the optimal parameters can vary widely depending on available data, the complexity of the hydrologic model and the tools available to optimize the parameters. This Appendix outlines the factors to consider and offers general guidelines for good practices to increase the robustness of hydrologic projections.

F.1 Hydrologic model selection

F.1.1 Prior considerations

Factors to consider when choosing an appropriate hydrologic model include the scope of the study, the type of results sought (relative comparison versus absolute values, extreme flow study (high versus low), seasonal or annual mean volume, etc.) and how the results will be used.

F.1.2 Types of hydrologic model and their limitations

A well-calibrated simple lumped model can successfully represent some hydrologic indices, such as annual or seasonal volumes. In some cases, however, a more complex distributed model may be more relevant. If a simulated river's streamflow is required, for example, or if the study involves a change in land use between the reference and future periods, a more complex distributed and physical model may be more appropriate. However, there is a trade-off between the more process-based approach versus a calibration-based approach. The larger number of inputs generally required for these models may not be available or may need to be estimated; these models are also more difficult to set up, and are typically more highly parameterized and harder to calibrate.

The choice of model must also be informed by the target watershed's dominant hydrologic processes. For example, a snowmelt-dominated watershed will require a snow accumulation and melt module that can adequately simulate the complexity of the dominant hydrologic process (Magand, 2014).

Another factor to consider is increase or decrease in the frequency of certain hydrologic events that have been little observed in the past. For instance, a model (or its parameters) may not be trained to reproduce warmth or rain-on-snow episodes if these are infrequent in the observed history.

It has also been shown that empirical equations used outside the conditions for which they have been established (e.g. future climate) can sometimes overestimate the value of the different components of the hydrologic cycle, such as evapotranspiration (Hajji et al., 2018; Ludwig et al., 2009). For this reason, it is important to use diverse calibration and validation periods, each with a range of wet to dry years to produce a more robust parameter set. It may also be important to consider a model's approaches for simulating various processes, for example, the use of potential evapotranspiration in modeling evaporation (Savenije, 2004). Ideally, choosing a model that has already been shown to correctly reproduce flow rates in changing climate is recommended (Broderick et al., 2016).

F.2 Calibration of hydrologic model parameters

Calibration is the process of estimating model parameter values to enable a hydrologic model to match observations such as runoff or streamflow (Kumarasamy and Belmont, 2018).

The process is usually carried out automatically using an optimization algorithm where the value of one (or more) objective function is to be minimized between the simulated and observed flows. Traditionally, the optimal parameters chosen are those that minimize the value of the objective function. In climate change hydrologic-impacts studies, the parameters are used in extrapolation mode and are assumed to adequately model the flows resulting from climatic scenarios. Thus, to ensure robustness in hydrologic projections, factors other than the value of the objective function must be taken into account when choosing the parameters.

Other methodologies, such as those oriented towards the reproduction of hydrologic processes, are also available to help inform the optimization process. The following section presents different ways to use valuable information in the calibration process, as well as various avenues to avoid choosing optimal parameters solely on the basis of optimization performance. The many challenges of parameters selection are also discussed here.

F.2.1 Optimization methods

To adequately address calibration issues for climate change impact studies, many solutions have been proposed in recent decades. Improvements in calibration procedures for hydrologic models can be separated into two closely interconnected categories: modifying optimization techniques and relying on complementary data for calibration. The first category, presented in **Section F.2.1.1**, includes techniques such as multi-objective calibration and the use of constraints. The second, presented in **Section F.2.1.2**, involves the use of measured or complementary data (evapotranspiration, snow water equivalent and soil moisture content) in the calibration procedure.

Considering interactions between parameters

Independently from their nature, all models use several equations and are, at some point, conceptual (Coron et al., 2011). Furthermore, since all parameters cannot be measured, calibration is an inevitable step when conducting a hydrologic study. Equifinality and interdependencies among parameters are well-known facts in hydrology (e.g. Kumarasamy and Belmont, 2018). Challenges such as dependency of model parameters on the climate of the calibration period and the low identifiability of parameter values (Coron et al., 2011) must also be considered. The correlation between parameter and climate indices have been studied and it has been shown that some parameters correlate much more closely with climate indices than other parameters. Merz et al., (2011), for example, showed that snow and soil parameters correlated particularly strongly with changing climate conditions. When a hydrologic model is used to perform climate change hydrologic projections, particular attention must be paid to calibration steps and parameter selection.

- Hierarchical selection of parameters during calibration can be used as a way to better understand the identifiability of the parameters (Kumarasamy and Belmont, 2018) and/or to better reproduce extreme (high and low) flows (Onyutha, 2019).
- Time-variable parameters can be considered as a way to improve the transferability of the parameter set, especially when using simple models with few parameters (Zeng et al., 2019).

Input data and other valuable information in the calibration process

Streamflow, temperature and precipitation observations are the minimum observed input data typically used to calibrate a hydrologic model. While it may seem obvious to utilize only the best available data prior to adjusting parameters to achieve desired performance metrics (Kumarasamy and Belmont, 2018), practitioners should also consider all available relevant information in the calibration process. If observed data (other than runoff or streamflow) are available for any of the hydrologic processes simulated by the model (e.g. snow measurements validating the snow accumulation and melting module, snow water equivalent, average evapotranspiration measurements from field instruments or satellite data, soil humidity data, etc.), these data, assuming quality control, can be used to validate the identifiability of the parameters of the model's hydrologic processes. Such types of information can also be used to restrain the model by imposing constraints during the optimization procedure (M Minville et al., 2014) and thus improve the model's robustness.

Several ways of incorporating additional data during optimization have been successfully explored.

- Gupta et al., (1999) showed that a multi-criteria calibration approach can be effective in constraining parameter estimates to physically plausible ranges, when observations on at least one appropriate heat flux and one properly selected state variable are available.
- Yapo et al., (1998) stated that exploiting useful information about the physical system contained in measured data time series can be employed for efficient multi-objective calibration procedures.
- Yadav et al., (2007) proposed a method that provides behavioural parameter sets for prediction of streamflows at ungauged basins. The method constrains the parameter space using hydrologic indices, with the constraints obtained by performing a regionalization of discharge characteristics.
- Zhang et al., (2008) also identified behavioural parameter ensembles using hydrologic indices in a multi-objective optimization framework.
- Bergstrm et al., (2002), and Cao et al., (2006) found that model results with measurements other than streamflow can lead to increased confidence in the physical relevance of hydrologic models.
- Immerzeel and Droogers (2008) put forward a calibration method for a conceptual and distributed hydrologic model where modelling monthly actual evapotranspiration (AET) is constrained by satellite data. They showed that in the best performing optimization, the R2 values between monthly sub-basins simulated and measured AET increase considerably.
- Khadam and Kaluarachchi (2004) indicated that relying on soft information, in their case the coefficient of efficiency of groundwater table records, can improve hydrologic model calibration.
- Fleming and Neary (2004) and Bennett and Peters (2004) suggested constraining parameter search space based on physically-based data. Their methodology uses soil, land and other geographic information system-based data for estimating values/ranges of HEC-HMS parameters. This helps limit the search space and improves efficiency.

F.2.2 Parameters selection challenges

Selecting optimal parameters set

When several sets of optimal parameters are available, it may be the case that only one (or a few) are used to carry out hydrologic impact studies. This section examines various approaches to selecting from several optimal sets.

- While it may be useful to use standard hydrologic metrics (Nash-Sutcliffe model efficiency (NSE) coefficient, Root Mean Square Error (RMSE)), hydrologic indices should also be used to help characterize the hydrograph and to refine the goal of the project (Olden and Poff, 2003). It is also important to keep in mind that the hydrologic indices identified as the most important for the study might be best reproduced by a set of parameters that are not considered optimal with respect to the standards metrics. Visual inspection by a trained hydrologist can help to identify parameter sets most appropriate to the type of study.
- Using regionalized parameters or regionalizing physical variables of the basin (Yang et al., 2019) reduce spatial discontinuities in the parameter field (as opposed to a strict basin-by-basin approach) and may help reproduce patterns which will better correspond with climate characteristics, such as aridity (PET/P) and runoff ratio (Q/P). Such a more physical approach can give more confidence in the robustness and transposability of the model.
- Averaging multiple model simulations often improves hydrological model performance (e.g. Arsenault, Essou, and Brissette, 2017; Arsenault, Gatien, Renaud, Brissette, and Martel, 2015; Seiller, Anctil, and Perrin, 2012), in terms of both multiple hydrological models and of simulations from multiple optimal parameters sets for a model. A variety of approaches for averaging ensembles or subsets of model simulations are available from literature.
- Although calibration is possible over the entire data period (Arsenault et al., 2018), a split-sample approach is often taken where the model is calibrated to one period and validated to another period. A Differential Split-Sample Approach (DSS, see below), where contrasted cycles are deliberately chosen within the observation dataset, is one approach to evaluate the robustness of a model and its potential to be transposed to a period with different climatic conditions.

More details about the DSS can be found in KlemeŠ (1986) and Refsgaard et al., (2014). These studies recommend DSS to ensure that the hydrologic model can properly simulate the hydrologic processes of interest under different climates. KlemeŠ (1986) describes it as follows:

"Two periods with different values of the climate parameters of interest should be identified in the historic record, e.g. one with high average precipitation, the other with low. If the model is intended to simulate streamflow for a wet climatic scenario then it should be calibrated on a dry segment of the historic record and validated on a wet segment. If it is intended to simulate flows for a dry climate scenario, the opposite should be done. In general, the model should demonstrate its ability to perform under the transition required: from drier to wetter conditions or the opposite."

Remembering the transposability aspect of hydrologic parameters

Hydrologic models are often criticized for being inadequate when used in extrapolation mode (Thirel et al., 2015). The transposability issue can even be more severe for climate change impact studies. In this context, the calibration and selection of hydrologic model parameters is of primary importance when integrating climate change data into the value modelling chain. For example, the findings of Her et al., (2019) suggest that the selection of both climate scenarios and hydrologic model parameters should be made carefully to improve the robustness of a hydrologic assessment of climate change.

Different sets of calibrated model parameters can yield divergent hydrologic simulations, which in turn can lead to different operational decisions and scientific conclusions. To obtain reliable hydrologic results, proper calibration is therefore fundamental (M Minville et al., 2014). Indeed, even if calibration of observed records provides reliable estimates of model parameters for current conditions, there is always the possibility that parameters estimated are not indicative of watershed behaviour in a different climate (Singh et al., 2011).

F.3 Calibration of an ungauged watershed

The calibration of a hydrologic model for an ungauged watershed is an additional challenge. The practitioner is referred to Winsemius et al, (2009), Wagener and Montanari (2011) Hrachowitz et al., (2013) for this subject as it is beyond the scope of this document.

Appendix G – Validation of hydrologic simulations

This appendix provides the practitioner with a comprehensive approach to evaluating the adequacy of hydrologic simulations and their robustness when projecting the impacts of climate change. The approach will help determine the suitability of the hydrologic simulation for the valuation modeling chain. **Section G.1** presents general concepts of the approach, **Section G.2** describes its limitations and **Section G.3** provides more in-depth information.

G.1 General concepts

The approach is based on the idea that for a simulation to adequately evaluate an asset's value, it must meet certain requirements when compared to the baseline. This approach is considered most reliable at the watershed scale and superior to the approach of using ensembles of simulations disregarding their performance (Krysanova et al., 2018).

The approach supports the vision that: " [...] it is the model's performance at the location of interest in the period with observations that is important, and not whether or not the model was calibrated and validated to that location. Sometimes a non-calibrated model may perform well enough, and the calibration may lead to problems related to over-tuning (Krysanova et al., 2018)." This vision can also be extended to say that the approach suits evaluations of hydrologic simulations coming from all types of hydrologic models, and both the streamflow and runoff variable of gridded hydrologic model. See **Section 5.5** – Hydrologic simulations for more information about the proper use of the runoff variable.

During the process, hydrologic simulations are compared with the hydrologic baseline over the time period of the hydrologic baseline (**Section 4.2**) and must meet minimum performance and robustness standards. The comparison needs to be made with several hydrologic indices to illustrate the numerous properties of hydrologic time series to which hydroelectricity production is sensible. The approach suggested is highly based on Krysanova et al., (2018).

This approach should be applied to any hydrologic simulation to better understand the strengths and limitations of the time series. It is also suggested for hydrologic simulations produced by the practitioner, as most of the time, the objective function for model calibration will only evaluate the hydrologic time series under a limited scope.

The comprehensive approach suggested is well suited for business decisions that necessitate much attention to details. The approach can also be carried out partially for other business decisions according to the practitioner's expertise.

The approach can be used specifically to:

1) Evaluate the performance of a hydrologic model to represent past hydrology
2) Evaluate the performance of a hydrologic model to represent hydrology on climatic scales (e.g. 30 years)
3) Evaluate the performance of various weather datasets (weather stations, gridded observations and reanalysis) in the hydrology model
4) Evaluate the performance of climatic simulations in the hydrology model on the reference period.

Note that evaluation of the input data to the hydrologic model as suggested in 3) and 4) should be done after the validation of the climate products as suggested in **Appendix E** – Validation of climate products (Krysanova et al., 2018).

G.2 Limitations

The limitations of the suggested approach are discussed below.

- The approach is limited by the availability of a hydrologic baseline. Hydrologic simulations of an ungauged watershed may still be carried out, but evaluation of their performance must rely on other methods.
- The approach is limited by the quality and the uncertainty of the hydrologic baseline. As discussed in **Section 4.2** – Hydrologic baseline, the baseline can present errors and uncertainty.
- Thresholds are proposed to represent the minimum performance. Those thresholds were proposed by Krysanova et al., (2018), but were not specifically designed for the evaluation of assets. Also, "[...] flexibility and pragmatism should be used in applying these thresholds, as the potential to achieve a certain model performance is dependent on the quantity and quality of data available, the catchment size, anthropogenic impacts, climate conditions and the flow regime (Krysanova et al., 2018)."
- The approach suggests carrying out differential split-sample testing (KlemeŠ, 1986; Refsgaard et al., 2014) as an approach to evaluate model robustness in addition to evaluating overall model performance during the period of the hydrologic baseline. However, the practitioner must balance the results of the two tests. Krysanova et al., (2018) emphasize that "[...] the ability of a model to maintain consistent performance across varying climatic periods (e.g. in a differential split-sample approach) is more important than extremely high performance in one period, as the level of performance across multiple periods is more indicative of the model's potential consistency in a future climate."

G.3 Methods

G.3.1 Defining the type of validation

The first step is to define the type of validation: systematic and/or the climatic. Regardless of type, the same time period (concomitant years) should be used while carrying out the validation to avoid inconsistencies due to low natural variability cycles and to climate change signal.

- The systematic validation can be carried out when the climate data fed into the hydrologic model correspond to past climate data. In this situation, the climate data come either from meteorological gauges, gridded observations or reanalysis products. Validation will be carried out for specific uses 1 and 3.
- The climatic validation is carried out when the climate data fed into the hydrologic model correspond climatically to past climate (climate projections, see Taylor et al., 2012). In this situation, the climate comes from climate models or weather generators. It will be carried out for specific uses 2 and 4.

Both types of validation are complementary. The practitioner might need to carry out both to support a sound business decision. For example, first evaluate the performance of a hydrologic model to represent past hydrology and then evaluate the performance of climatic simulations.

The same time period in the baseline and the simulations should be considered while carrying out either the systematic or climatic validation. It will avoid inconsistency due to low natural variability cycles and to climate change signal.

G.3.2 Validating the hydrologic simulations

Validation of hydrologic simulation is carried out using the four steps below. In the procedure, rejection criteria for a simulation are according to Krysanova et al., (2018). **Table G1** suggests specific implications regarding the rejection criteria for the valuation of assets. Rejection criteria proposed by Krysanova et al., (2018) are acceptable if the practitioner plans to use a delta, bias correction or extension method. With the direct method, the rejection criterion should to be much more restrictive. Rejection criteria are suggestions from the literature and project team. However, practitioners should consider the needs and objectives of their assessment and adjust these criteria according to their tolerance limits.

Table G1 Suggested specific rejection criterion for different hydrologic indices for direct, bias correction, delta and extension methods.

Hydrologic indices of interest	Rejection criteria for the delta, bias correction and extension methods. According to Krysanova et al., (2018).	Rejection criteria for the direct method. According to the project team.
Long-term annual average	25%	5%
Inter-annual variability	25%	25%
Nash-Sutcliffe efficiency (NSE)	0.5	0.7
Monthly average	25%	5%-10%
Monthly variability	25%	25%
Monthly correlation coefficient	0.8	0.8

1. General validation

1.1. Compute performance:

- Long-term annual average
  - Compute long-term annual average of Qobs & Qsim.
  - Rejection if over/underestimation > 25%
- Inter-annual variability
  - Compute annual average (AA) of Qobs & Qsim
  - Compute bias in standard deviation of AA-Qobs & AA-Qsim.
  - Rejection if bias > 25%
- Nash-Sutcliffe efficiency (NSE)
  - For systematic validation:
  - Rejection if NSE < 0.5

1.2. Plot graphs:

- Daily hydrographs (monthly if the hydrologic model is at a monthly time step)
  - Compute daily mean, minimum and maximum of Qobs & Qsim
  - Plot mean-Qobs and mean-Qsim over time. Do the same for minimum and maximum.
    - Is the mean hydrograph well represented by the simulation?
    - Are there problems with the minimum and maximum streamflows of the simulation?

- Long-term annual average
  - Compute annual average (AA) of Qobs & Qsim.
  - Plot AA-Qobs & AA-Qsim over time.
  - For specific uses 1 and 3:
    - Are there trends in AA-Qobs and AA-Qsim? Do they correspond with each other?
    - If there is a trend in either AA-Qobs and AA-Qsim, its possible causes need to be studied. See **Appendix B** – Detection and attribution in the context of climate change.
    - If the trends in AA-Qobs & AA-Qsim do not correspond with each other and cannot be explained by cause, further investigation is needed.
  - For specific uses 2 and 4:
    - Are there trends in AA-Qobs? What are their causes?
    - Trends in AA-Qsim, if the driving simulation comes from a GCM, need to be evaluated with the ensemble approach because of natural variability. (Maraun and Widmann, 2018)

2. Validation of simulations for every hydrologic indices of interest (Appendix G.3.3 – Defining hydrologic indices)

2.1. Compute performance for each hydrologic index

- Example for monthly average
  - Compute monthly average (MA) of Qobs and Qsim
    - Rejection if over/underestimation > 25%
  - Compute standard deviation of MA-Qobs and MA-Qsim.
    - Rejection if bias > 25%
  - For systematic validation:
    - Compute coefficient of correlation between MA-Qobs and MA-Qsim
    - Rejection if $r < 0.8$
- If the simulated dataset does not perform adequately for a hydrologic process, it represents a limit of the dataset. The dataset should not be used to project this hydrologic process in the future.
- Results can also be compiled visually with heatmaps (see example of heatmaps in **Appendix E** – Validation of climate products).

3. **Differential Split-Sample Approach (DSS)**

3.1. Compute the performance as in 1.1 and 2.1 according to DSS. See **Appendix G.3.1** – Defining the type of validation for more information on the DSS.

- If the practitioner carries out the calibration of the model alone, it is recommended to run the DSS during the calibration process.
- If the practitioner does not carry out the calibration alone, the DSS should still be carried out by validating the output of the model for two periods with different values of the climate parameters.

4. **Validation at multiple sites and on multiple variables**

- Carry out validation similar 1), 2) and 3) at multiple sites and on multiple variables (e.g. snowmelt, evapotranspiration, etc).

G.3.3 Defining hydrologic indices

The list of hydrologic indices can change according to asset type (reservoir/run-of-river), size of the watershed, revenue type (energy, power and ancillary services), etc. The list below presents indices that are generally of interest to hydroelectricity producers. The practitioner can also use the baseline and sensitivity analysis presented in **Appendix H** – Sensitivity Analysis to identify its own indices or to prioritize the one from the list below.

- Annual, seasonal and monthly flow volumes (mean, distribution and timing)
- Inter-annual flow variability
- Intra-annual flow variability (monthly and/or seasonally)
- Inter-annual flow persistence
- Days with flows over a given threshold (e.g. exceeding powerhouse capacity)
- Multi-year hydrologic drought (function of streamflow)
- Number and timing of low flow days/weeks

Appendix H – Sensitivity Analysis

Sensitivity analyses enables the practitioner to get a sense of the how sensitive an asset's value is to the hydrology and/or climate (e.g. +/ – 10% annual inflow). It helps to clarify important hydrologic/climatic processes underway in the watershed.

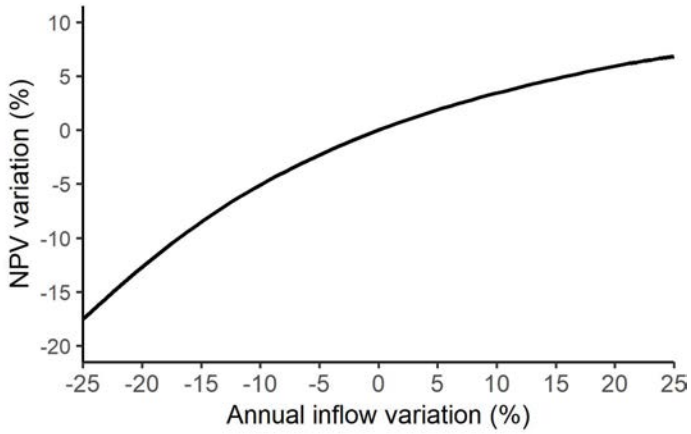
It also enables the assessment of the value's sensitivity to hydrology and/or climate relative to other factors (e.g. export prices, discount rates, etc). This exercise can inform decisions about how much effort to put into the climate change studies suggested in this Guidebook.

The sensitivity analysis consists of varying some properties of the baseline time series, such as mean or extremes, and identifying the resulting impacts on the rest of the modeling chain. A similar exercise can be carried out if models are available. Watershed conditions, water management scenarios, energy prices, etc. can all be modified in their respective models to see the impacts in the rest of the modelling chain.

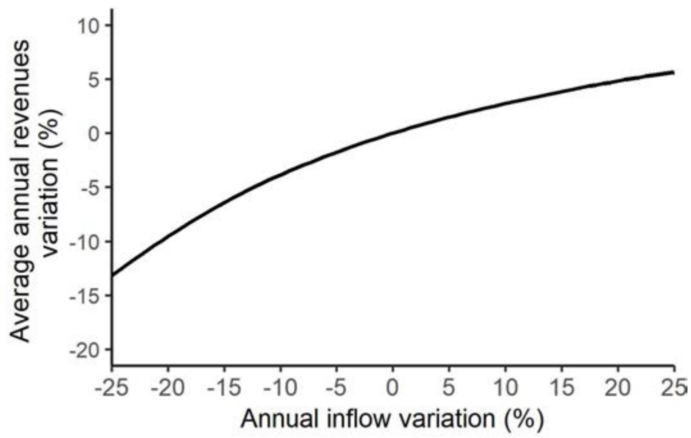
Appendix G – Validation of hydrologic simulations presents a list of hydrologic indices that represent typical important hydrologic processes of interest for the evaluation of assets. Appendix E – Validation of climate products presents a similar list for climate indices.

Figure H1 shows an example of sensitivity analysis. In this example, the NPV is more sensitive to variation in annual inflows than to variations in mean revenues. Mean revenues are also more sensitive to variation in annual inflows than to variation in low flows.

A)



B)



C)

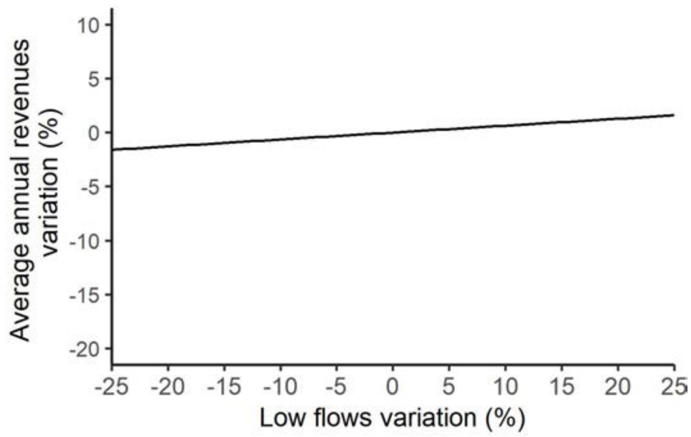


Figure H1 Example of sensitivity analysis with the hydrologic baseline for A) the NPV vs. annual inflow rate, B) average annual revenues vs. annual inflow rate and C) average annual revenues vs. low flows.

Appendix I – Best and good practices for the ensemble approach

This appendix provides recommendations for how many scenarios, models and methods to include when working with the ensemble approach. Selection may be driven by the goals and constraints of the practitioner, for example, time and resource limitations. If existing data/results are being reused, it is also necessary to assess whether a given ensemble size is sufficient by understanding how many scenarios/models are appropriate for a meaningful ensemble. This is a criterion to consider when selecting climate change data (**Section 5**). **Table I1** presents both best practices and good practices in terms of the number of scenarios/models that should be used. **Section 2.3** – Sources of uncertainty and **Appendix C** – GCM selection methods present complementary background information about ensembles and uncertainty, and GCM ensemble selection methods, respectively.

Table I1 Best and good practices for the ensemble approach. Several of the concepts mentioned here are supported by background information in **Section 2.3** – Sources of uncertainty.

	Best Practices	Good Practices
Emissions scenarios	The industry best practice is to use all available emissions scenarios from the most recently published group of emissions scenarios available. This is particularly important for longer lead times (e.g. > 50 years), where the choice of emissions scenario is likely to have a more significant impact on hydrologic projections (Ignazio Giuntoli et al., 2018).	A good practice to use at least two emissions scenarios: a moderate and a business-as-usual scenario (for CMIP5 these are RCP4.5and RCP8.5; respectively Van Uytven and Willems, 2018). For short lead times (< 15 years), it may be acceptable to use only one emissions scenario, because the climate signal may not yet have emerged (**Section 2.3** – Sources of uncertainty). If it is not possible to use newly published emissions scenarios, older scenarios are acceptable.
Global Circulation Models	The industry best practice has traditionally been to use as many GCMs as are readily available (the newest versions of the models if possible), because no single GCM consistently outperforms all others (IPCC, 2013). However, a few studies have suggested that it may be better to select certain models (Chen et al., 2016; Maraun et al., 2017; Maraun and Widmann, 2018). This is discussed further in **Appendix C** – GCM selection methods The challenge is that it is unclear how to select the best models and the results of sub-selections are difficult to interpret (Maraun et al., 2017). In the past, selection has sometimes been undertaken with limited information regarding quality and reliability (Her et al., 2019); hence, caution with selection is advised.	A good practice is to use fewer models (including older versions of the model if that is all that is available); however, it is crucial that a study not be conducted with too few models (see **Appendix C** – GCM selection methods). Unfortunately, there are few publications available that identify an appropriate minimum number of GCMs. The IHA recommends the use of three locally-credible GCM or RCM-based climate projections (optimistic, central, pessimistic; (IHA, 2019). Wang et al., (2018) found that the projections from 10 climate models are sufficient, and that little improvement is gained with more than 10 models. However, this assessment was based on covering the majority of the uncertainty. Assessments based on other criteria could suggest a different minimum number of GCMs (**Appendix C** – GCM selection methods). When several simulations of the same of the same GCM with the same emissions scenario (realizations) are available, a good practice is to select the first realization.
Hydrologic Models and Post-processing	The hydrologic model and post-processing steps of the modeling chain can be important contributors to total uncertainty (**Section 2.3** – Sources of uncertainty). Therefore, it is ideal to use several hydrologic models (e.g. Giuntoli et al., 2015; Hattermann et al., 2018) and post-processing methods (e.g. Chen, Brissette and Leconte, 2011; De Niel, Van Uytven and Willems, 2019). Regardless of the number of models used, it is important that key processes be represented and that the model be well calibrated (Krysanova et al., 2018).	It is often not feasible to use an ensemble of hydrologic models and post-processing methods. It may instead be more valuable (and more manageable) to use the correct type of model/method (**Appendix F** – Selection and calibration of a hydrologic model), with appropriate calibrations based on high-quality data (Chen et al., 2013b; Gao et al., 2019; Pechlivanidis et al., 2011). The practitioner's experience with the hydrologic model is important (also see **appendices E-G**).

Appendix J – Case Studies

Brookfield Renewable Case Study

Application of the Delta Method to the Penobscot and Susquehanna Watersheds for Future Climate Change Hydrology Scenarios

By: Nelson Jia, Bruno Benedetti and Andy Davis

Context

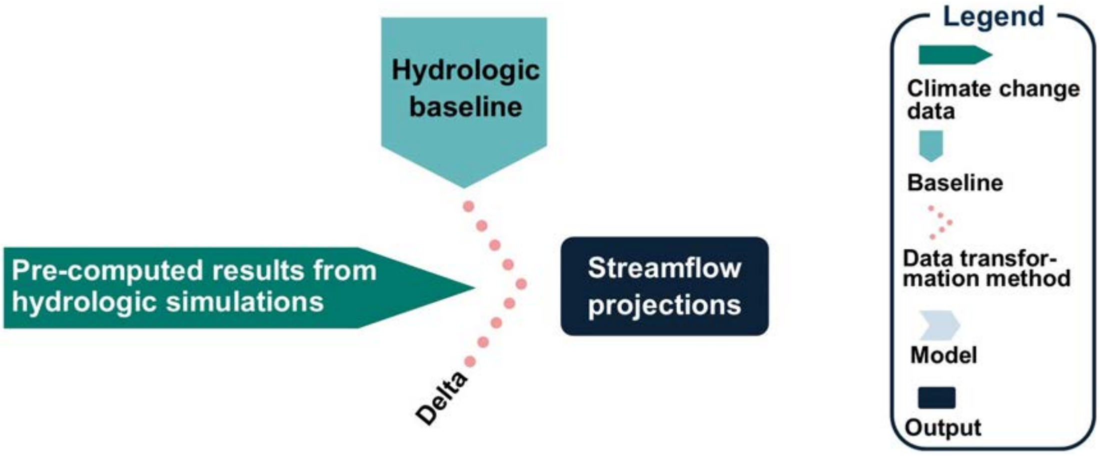
In line with its Environmental Social Governance program and its dedication to investing in renewable energy, Brookfield Renewable values the impact of climate change on the power generation potential of hydroelectric assets. The purpose of the case study is to show how the delta method described in Ouranos's Guidebook on Valuation of Hydropower Assets and Climate Change Physical Impacts (Fournier et al., 2020) can assist in developing streamflow projections under climate change scenarios. The case study was conducted on the Penobscot and Susquehanna watersheds, where Brookfield Renewable owns and operates many hydropower assets.

Objective

- Develop streamflow projections to show how climate change impacts flow in the Penobscot and Susquehanna watersheds.
- Demonstrate the applicability of the delta method and its ability to apply a pre-computed climate change hydrology scenario to a hydrology baseline and obtain future climate change streamflow projections.

Approach

The delta method involves a perturbation of the baseline using the relative or absolute change between the simulated reference and future periods within a given simulation integrating climate change. The perturbation is based on a pre-computed climate change impacted hydrologic scenario. The scenario is the product of a previously completed case study and was subjected to validation techniques to ensure it is applicable to the hydrology baseline.



Results

The case study was applied to two American watersheds: Penobscot (New England region) and Susquehanna (Atlantic seaboard). Literature review yielded two studies presenting pre-computed climate change hydrology scenarios: Hayhoe (2007) and Johnson (2015). The Hayhoe article computes its climate change hydrologic scenario with an estimated increase in runoff, while the Johnson article computes its climate change hydrologic scenario with an estimated increase in flow.

The pre-computed simulations were assessed by comparing them with the historical baseline flows from Brookfield Renewable, based on their average flows and standard deviations. To confirm the adequacy of the pre-computed climate change hydrology simulations, the difference between the average flows and between the standard deviations should each be less than 25%.

For the application of the Johnson (2015) article, the pre-computed climate change hydrologic scenarios came from the Merrimack and the Susquehanna watersheds, which were applied to the Penobscot and Susquehanna watershed baselines, respectively. The Merrimack watershed scenario passed the validation test, with differences in average streamflow of less than 15% and in standard deviation of approximately 20% compared to the Penobscot watershed's historical baseline flow. The Susquehanna watershed scenario was also deemed adequate, with a difference of approximately 25% between the historical baseline flows. However, the Hayhoe (2007) scenario was deemed inadequate, as the differences exceeded 25%.

Once the Johnson (2015) article results were successfully validated, the delta method was applied to the historical Penobscot and Susquehanna watershed baselines to obtain future climate change hydrologic projections. The average flow perturbations applied to the Penobscot and Susquehanna watersheds were +0.4% and +0.2%, respectively.

These estimated increases in flow represent valuable information that will help Brookfield Renewable make long-term business decisions related to investments, contract renewals, asset refurbishments and environmental interventions. However, a more in-depth analysis should be conducted to obtain more precise results.

Lessons learned

- The application of the case study worked best when using flow rather than runoff. Additionally, the watersheds used for the pre-computed and the baseline scenarios should be comparable to obtain valid results.
- The granularity and details of the applied perturbation depend on those of the selected studies.
- The delta method is fast, easy and convenient to use. However, the novice practitioner can get lost in the literature review (i.e. finding studies to establish the perturbation factor). The method would benefit from the establishment of a library of relevant studies.
- Criteria to establish hydrologic similarity between watersheds are very simple, yet only a limited number of reference watersheds is available. This restricts the extent to which the method can be applied. The method would gain from further studies on additional basins.

Reference

This case study was developped as part of the Guidebook: Fournier, E., Lamy, A., Pineault, K., Braschi, L., Kornelsen, K., Hannart, A., Chartier, I., Tarel, G., Minville, M. et Merleau, J. (2020). Valuation of Hydropower Assets and Climate Change Physical Impacts A Guidebook to Integrate Climate Data in Energy Production for Value Modelling, Ouranos, Montréal, 208 pages.

Hayhoe, K., Wake, C. P., Huntington, T. G., Luo, L., Schwartz, M. D., Sheffield, J., ... & Troy, T. J. (2007). Past and future changes in climate and hydrological indicators in the US Northeast. Climate Dynamics, 28(4), 381-407. https://doi.org/10.1007/s00382-006-0187-8

Johnson, T., Butcher, J., Deb, D., Faizullabhoy, M., Hummel, P., Kittle, J., ... & Sarkar, S. (2015). Modeling streamflow and water quality sensitivity to climate change and urban development in 20 US watersheds. JAWRA Journal of the American Water Resources Association, 51(5), 1321-1341. https://doi.org/10.1111/1752-1688.12308

Hydro-Quebec Case Study

Climate Change Impacts on Hydro-Quebec's Annual Water Inflow, Evolution of the Mean and Variability

By: Guillaume Jean Tarel[1], Catherine Guay[2], Marie Mainville[2]

Context

In a 2015 article, Guay et al. used the CMIP3 set to show, among other things, a probable future increase in mean annual streamflow in Quebec (Guay et al., 2015). To complete these results and assess the impact of climate change on the hydropower fleet, it is also important to characterize the probable evolution of the variability of inflows (HQD, 2019). This analysis is made using the simulations from the cQ2 project based on the CMIP5 climate set.

Objective

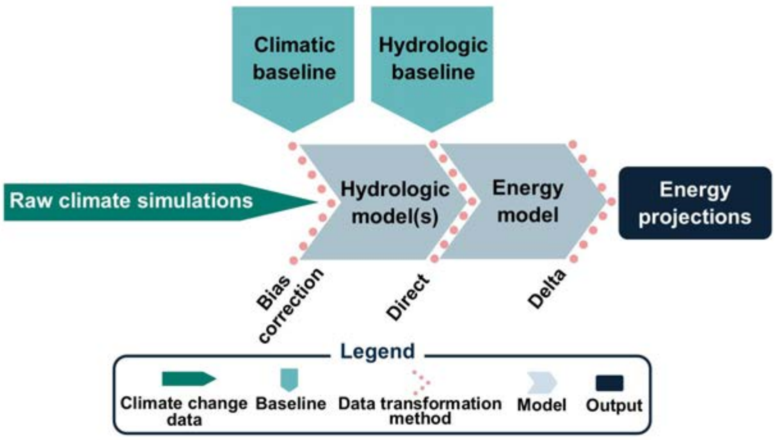
- Compare results obtained with CMIP5 to the previous simulations derived from CMIP3.
- Analyze the evolution of variability by 2050.
- Evaluate whether the available hydrological simulations accurately represent the sequences of years characterized by low runoff.

Approach

As part of the cQ2 project, CMIP5 climate simulations were used as inputs to a hydrological model (HSAMI) to produce simulations of future flows for several dozen sites in the HQP system. Two radiative forcing trajectory scenarios were taken into account (RCP 4.5 and 8.5). The initial step, adequacy analysis, validates whether the available data adequately reproduce the observed history (control period 1971–2000). The analysis showed that:

- the annual means and inter-annual variability, represented by the standard deviation, are suitable variables.
- the cumulative variables over several years (for example the sequences of years of low water levels) are not adequately represented by the available data.

In the light of these findings, the changes in annual means and inter-annual variability were therefore calculated using a delta approach, comparing the variables between the future period and the reference period. Changes in the sequences of years of low water levels have not been studied.

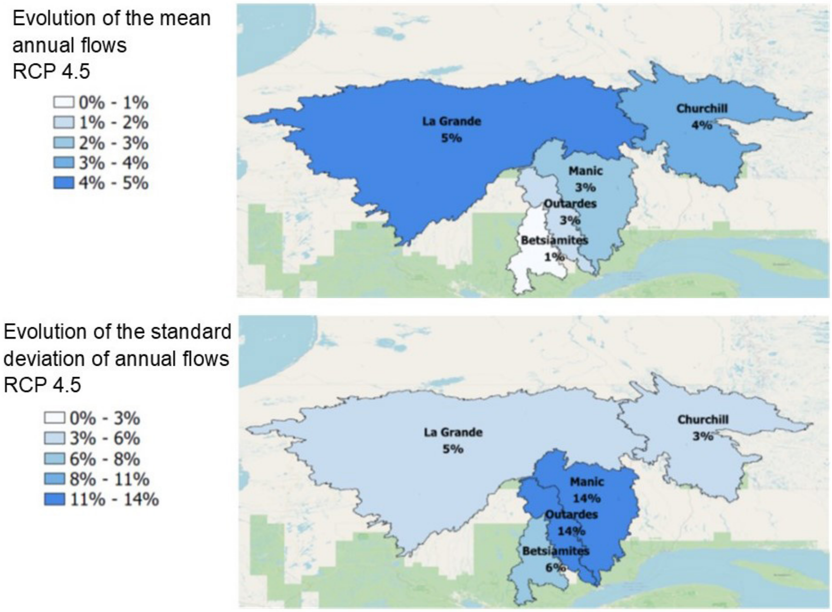


[1] Hydro-Québec Production, [2] Centre de recherche d'Hydro-Québec

Results

Note: The results below are presented in terms of the probable future change in annual mean flows. As the conversion efficiencies of the flows into energy are vary between different facilities, it is not possible to directly transpose the evolution of the flows into an energy evolution. Moreover (see above), the evolution of the sequences during years of low water levels has not been studied.

In terms of flows, the annual means show an increase between the control period (1971–2000) and the future period (2036–2065). The figure below provides more detail about the most important basins (for the RCP 4.5 scenario). The changes are of the same order of magnitude as obtained in Guay et al. (2015). As the mean increases, so do the standard deviations in the case of RCP 4.5. Even in the case of RCP 8.5, the standard deviations increase considerably more than the means. This results in an increase in the variability of flows from year to year.



Lessons learned

- This type of assessment is not trivial and there is a relatively high risk of making faulty conclusions using inappropriate data (Fournier et al., 2020)
- Conducting an adequacy analysis of simulations, comparing the simulations with available history, is essential and should be recommended to all users. Relying on external expertise or the Ouranos Guidebook on Valuation of Hydropower Assets and Climate Change Physical Impacts (Fournier et al., 2020) is also recommended.
- For Hydro-Quebec Production, the analysis of the available simulations showed that it is necessary to further study the sequences of years of low water levels.

Reference

This case study was developped as part of the Guidebook: Fournier, E., Lamy, A., Pineault, K., Braschi, L., Kornelsen, K., Hannart, A., Chartier, I., Tarel, G., Minville, M. et Merleau, J. (2020). Valuation of Hydropower Assets and Climate Change Physical Impacts A Guidebook to Integrate Climate Data in Energy Production for Value Modelling, Ouranos, Montréal, 208 pages.

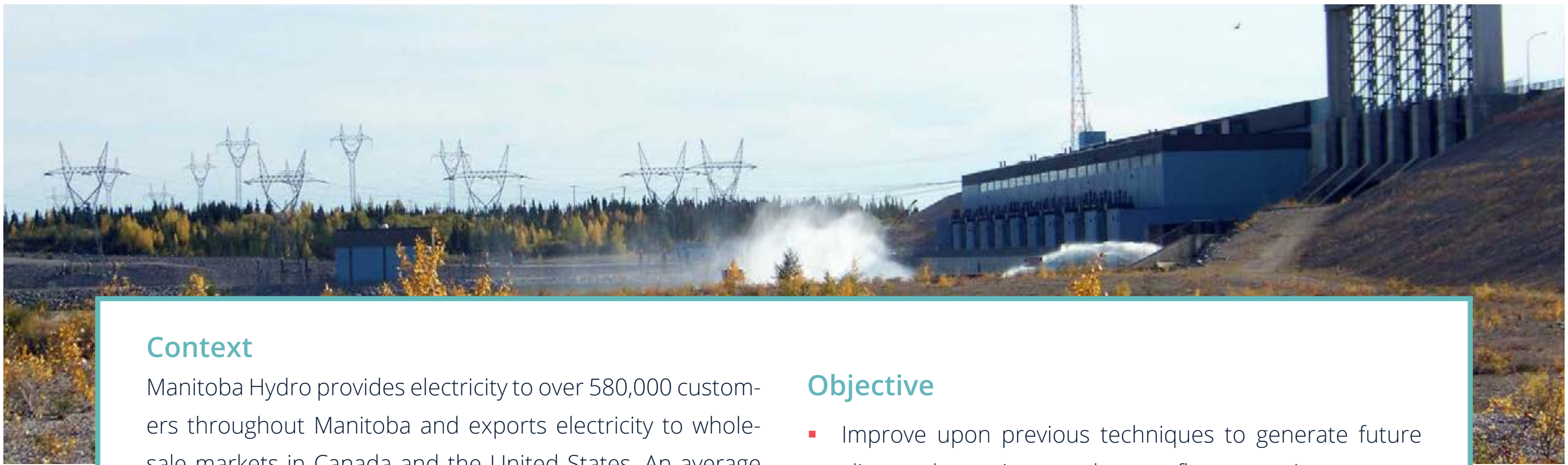
Guay, C., Minville, M., and Braun, M. (2015). A global portrait of hydrological changes at the 2050 horizon for the province of Québec. Canadian Water Resources Journal, 40(3), 285–302. https://doi.org/10.1080/07011784.2015.1043583

Hydro Québec Distribution. (2019, Novembre 1). Complément d'information du plan d'approvisionnement 2020-2029. http://publicsde.regie-energie.qc.ca/projets/529/DocPrj/R-4110-2019-B-0009-Demande-Piece-2019_11_01.pdf

Manitoba Hydro Case Study

Exploring Climate Change Considerations for Evaluating Generating Station Upgrades

Contact details: Kristina Koenig, kkoenig@hydro.mb.ca



Context

Manitoba Hydro provides electricity to over 580,000 customers throughout Manitoba and exports electricity to wholesale markets in Canada and the United States. An average of 96 per cent of the electricity it generates annually comes from 15 hydroelectric generating stations, primarily on the Winnipeg, Saskatchewan and Nelson rivers.

With guidance from Ouranos, Manitoba Hydro Water Resources Engineering and Resource Planning professionals collaborated to explore the integration of climate change scenarios into existing hydrological modelling and resource planning modelling frameworks. This exercise merged climate science with industry practices to explore the topic pragmatically.

Objective

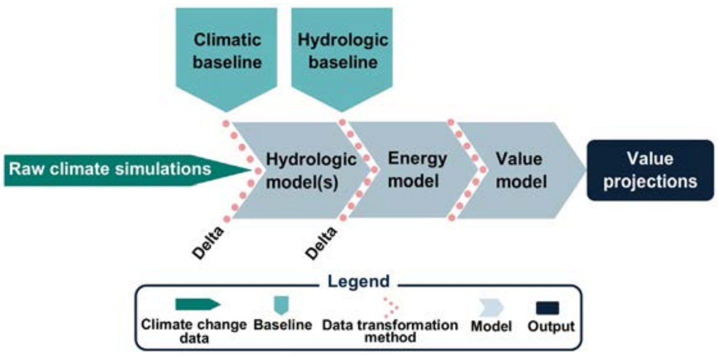
- Improve upon previous techniques to generate future climate change impacted streamflow scenarios.
- Generate future streamflow scenarios and test how these may be used in resource planning.
- Explore the impact of future streamflow scenarios on a potential generating-station upgrade.
- Investigate the process to integrate future streamflow scenarios into resource planning models.

Approach

Starting with an ensemble of 40 climate model simulations (Manitoba Hydro, 2020), projected changes in precipitation, minimum, and maximum temperature were combined with a climatic baseline to generate future climate scenarios for the 2050s across the Nelson-Churchill watershed (1.4 million km^2). Future climate scenarios were then used to drive WATFLOOD distributed hydrologic models to produce future streamflow scenarios.

Uniquely positioned with Long Term Flow Data (LTFD; 106 year hydrologic baseline), the approach was tailored to use LTFD, which is fundamental to resource planning studies. WATFLOOD streamflow scenarios were used to develop a set of quantile-based future flow correction factors (deltas) to assess changes in means, extremes and variability. Deltas were applied monthly, seasonally and semi-annually to generate future LTFD scenarios.

To best utilize computational and staff resources, cluster analysis was used to select a subset of six future LTFD scenarios that represent a broad range of energy-production impacts. The subset was used to drive a suite of resource planning models to evaluate energy and economic impacts of various upgrade options under future streamflow scenarios.



Results

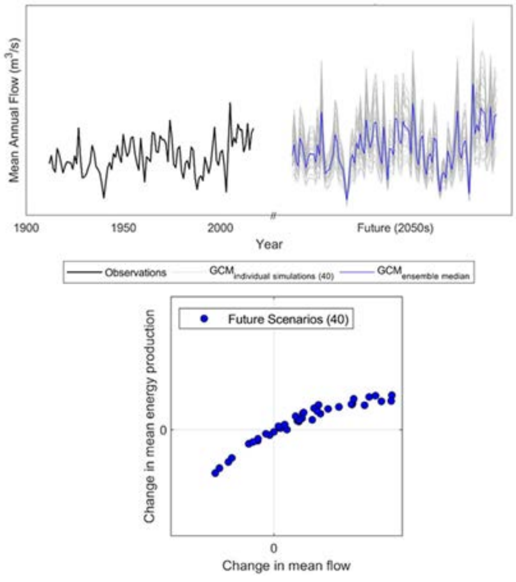
WATFLOOD hydrologic models were developed and calibrated to a range of historical conditions. Due to uncertainties in simulating future regulation, models were configured to simulate natural conditions at key flow index locations.

Adjustment factors from quantile maps, comparing baseline to future (2050s; 2040-2069) WATFLOOD output, were applied to create future LTFD scenarios. Due to the LTFD record length, a de-trending/re-trending approach was followed, but this step remains an area for further study.

Overall, the ensemble of 40 future LTFD scenarios tend towards wetter conditions, but some scenarios indicate decreasing flows. Using a screening level energy production model, LTFD scenarios were evaluated for changes in mean annual energy production. Results show that flow increases generally lead to increases in energy production but begin to plateau as flows approach powerhouse capacities. A cluster analysis algorithm was used to select a sub-set of six scenarios for further analysis, capturing 97.3% of the ensemble range in future energy production change. The sub-set is important since it is computationally and time prohibitive to evaluate all scenarios in a detailed resource planning modelling framework.

The sub-set of future LTFD scenarios were run through a suite of resource planning tools. LTFD scenarios were first run through a coarser resolution system wide production model which simulates reservoir operations, electricity generation and export revenue using inputs such as a load forecast, export price forecast and operational limitations. Outputs from this model inform a production model with representation of individual generating station unit operations. For exploratory purposes, climate change impacts are considered in isolation of other effects, as only LTFD and upgrade options were changed from baseline conditions.

This process allows testing of various generating station upgrade options for comparison against one another under baseline conditions and with climate change. In this preliminary work, upgrade options were found to be economically robust using baseline LTFD and when future climate change scenarios were integrated.



Lessons learned

- Early collaboration between areas of expertise (climate science, hydrology, energy-production modelling) was instrumental in project execution and in refining the methodology.
- While many sources of uncertainty exist in hydrologic and energy modelling, exploring the scope of impacts coming from future climate scenarios can be a valuable sensitivity analysis.
- While climate change impacts on streamflow can affect project economics, other factors, such as capital costs, energy prices and discount rate were found to be more significant factors.
- Multi-year hydrological drought plays an important role in long-term resource planning. Understanding the climate change impacts on these unique extreme events is of interest for future work.

Reference

This case study was developped as part of the Guidebook: Fournier, E., Lamy, A., Pineault, K., Braschi, L., Kornelsen, K., Hannart, A., Chartier, I., Tarel, G., Minville, M. et Merleau, J. (2020). Valuation of Hydropower Assets and Climate Change Physical Impacts A Guidebook to Integrate Climate Data in Energy Production for Value Modelling, Ouranos, Montréal, 208 pages

Manitoba Hydro (2020, March). Manitoba Hydro's Climate Change Report. https://www.hydro.mb.ca/environment/pdf/climate_change_report_2020.pdf

Ontario Power Generation Case Study

The Impact of Climate Change on a Redevelopment Scenario

By: Kurt C. Kornelsen

Context

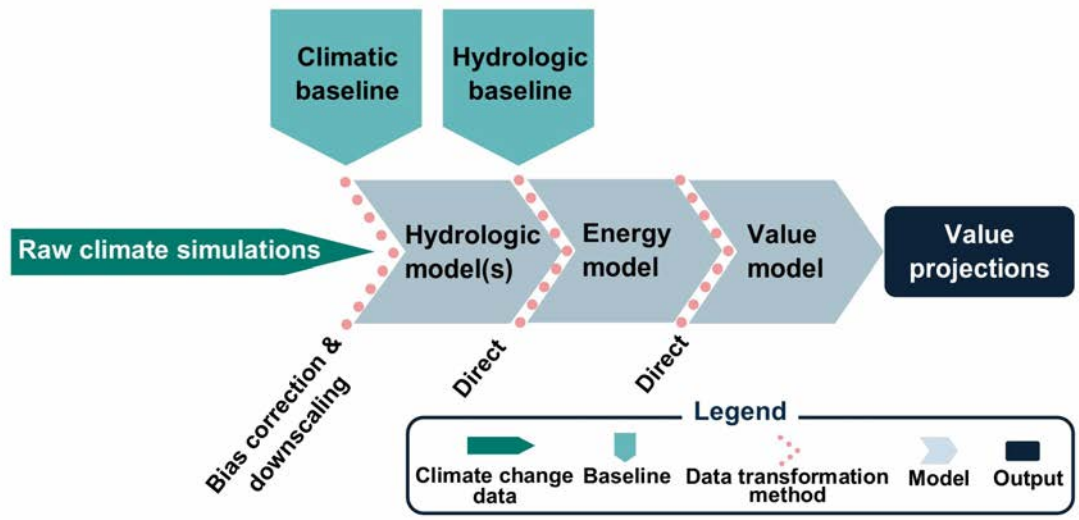
Business cases for the construction or redevelopment of generating stations need to reflect revenues and costs over the long lifespans of hydropower assets. This case study involved a nearly end-to-end assessment of potential changes in streamflow and energy production caused by climate change and the impact these could have on the current costs of a hypothetical project.

Objective

Develop an understanding of the impacts of climate change on the energy production of an individual station and their relative influence on the valuation of station redevelopment.

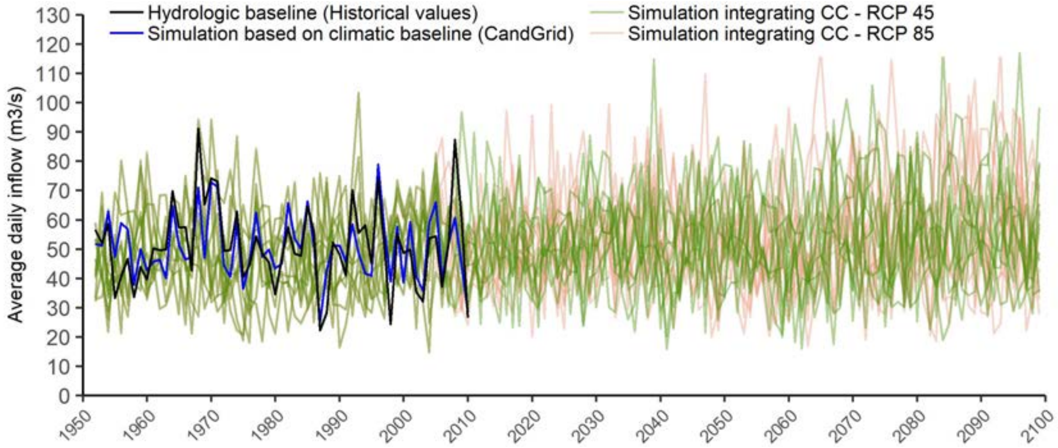
Approach

To better isolate the impacts of climate change from other influences, such as changes in reservoir management, OPG decided to implement the full modelling chain and climatic baseline. Downscaled and bias-corrected GCM scenarios for temperature and precipitation were provided by Ouranos and used to simulate daily flow and energy production from the generating station. A financial model was used to determine the relative impact that climate-driven flow changes could have on station valuation. Operational or physical adaptations were not considered.



Results

- Several iterations of the hydrologic model were used to enhance consistency with historical data and simulation based on a climatic baseline, resulting in a well-performing modelling chain with an inflow bias of less than 1% compared to historical values. This was achieved by calibrating the hydrologic model over a longer historical period of 62 years and by using the same base-gridded precipitation product used as reference for climate-data bias correction.
- Mean annual flow was not found to be affected much at this site as a result of climate change (i.e. few significant trends), but there is greater year-to-year variability in flow, as well as more frequent high- and low-flow years, although they are of similar magnitude to historical records (Figure). Flow changes had a corresponding impact on energy production.
- The asset valuation was sensitive to many factors unrelated to climate, including investment cost and discount rate. Some of these financial factors were found to affect projected asset value more than the anticipated variations in energy production due to climate change. It should be noted that physical or operational adaptation measures were not considered as part of this case study and would impact project costs and energy production.
- A sensitivity analysis on energy-production values revealed that the valuation was more sensitive to lower energy production than it was to higher energy production.



Lessons learned

- Several models are involved in the modelling chain that produced the final outcome. It was helpful to put all the pieces together, using acceptable-quality models, and then perform a sensitivity analysis on the whole chain to identify which models most influenced the final results. This enabled us to better focus our efforts and refine the few models that had the biggest impact on the final outcome.
- Consistency proved to be very important. It was absolutely necessary to recalibrate our hydrologic model using the same gridded precipitation product used as reference for the GCM bias-correction method, as the original hydrologic model was calibrated with different datasets. The shared baseline removed some significant initial biases.

Reference

This case study was developped as part of the Guidebook: Fournier, E., Lamy, A., Pineault, K., Braschi, L., Kornelsen, K., Hannart, A., Chartier, I., Tarel, G., Minville, M. et Merleau, J. (2020). Valuation of Hydropower Assets and Climate Change Physical Impacts A Guidebook to Integrate Climate Data in Energy Production for Value Modelling, Ouranos, Montréal, 208 pages.