Characterizing uncertainty of the hydrologic impacts of climate change

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Abstract

The high climate sensitivity of hydrologic systems, the importance of those systems to society, and the imprecise nature of future climate projections all motivate interest in characterizing uncertainty in the hydrologic impacts of climate change. We discuss recent research that exposes important sources of uncertainty that are commonly neglected by the water management community, especially, uncertainties associated with internal climate-system variability and hydrologic modeling. We also discuss research exposing several issues with widely used climate downscaling methods. We propose that progress can be made following parallel paths: first, by explicitly characterizing the uncertainties throughout the modeling process (rather than using an ad-hoc "ensemble of opportunity"); second, by reducing uncertainties through developing criteria for excluding poor methods/models, as well as with targeted research to improve modeling capabilities. We argue that such research to reveal, reduce and represent uncertainties is essential to establish a defensible range of quantitative hydrologic storylines of climate change impacts.

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1 Introduction

Many planning and management decisions require an understanding of the vulnerability of hydrologic systems to a wide range of different stresses. A key challenge is to identify defensible options for the design and operation of systems under an uncertain and changing climate [Milly et al. 2008]. In the water resources sector, this requires defining a range of different climate change scenarios in order to evaluate the vulnerability of infrastructure systems and the effectiveness of different adaptation strategies in managing climate-related stresses [Wilby and Dessai 2010; Brown et al. 2012]. For many users, the range of climate scenarios is most compatible with decision making processes when it is distilled into a set of discrete quantitative hydrologic "storylines" of climate change impacts, each representing key features from the full range of possible climate scenarios. While much of this paper will focus on the implications for the water resource sector, the lessons here extend across all of hydrology, and more generally, to any other field that is grappling with projecting the impacts of climate change.

Developing quantitative hydrologic storylines of future change for the water sector is an interdisciplinary endeavour – it entails representing current knowledge of global change in the context of substantial uncertainty in the trajectory of future climate and the associated impacts on hydrologic processes. Recent research has shown the importance of assessing uncertainty from a large number of sources (Figure 1; see also Section 3), including, global model structure [Meehl et al. 2005; Knutti and Sedláček 2013], internal climate variability [Deser et al. 2012a; Deser et al. 2012b], climate downscaling methods [Mearns et al. 2013; Gutmann et al. 2014] and hydrologic models [Addor et al. 2014; Mendoza et al. 2014; Vano et al. 2014; Mizukami et al. 2015]. Increasing computational resources permit more sources to be combined, such that model ensemble sizes have grown from a handful of experiments a few decades ago to hundreds of projections now. This plethora of available projections and methodological options is outpacing the ability of the applications community to handle large ensembles and thereby comprehensively characterize uncertainty [Christierson et al. 2012]. Furthermore, it is critical to keep the application community engaged and informed to ensure that this plethora of science information can be translated into actionable water resources planning and operational decisions.

This paper provides a critical review of capabilities to characterize and understand uncertainty in the hydrologic impacts of climate change (excluding changes in water management). We conduct our review in the context of a paradigm shift in water resources planning, namely a move toward a structured decision making (SDM) framework that tests the performance of different options that are highlighted within an envelope of broad uncertainty [Lempert et al. 2004; Brown et al. 2012; Yates et al. 2015]. Specifically, we ask *why* research is needed to characterize uncertainty in climate change impacts on hydrology (Section 2). We consider societal motivations for appraising the potential impacts of climate change in water resources planning and management, as well as scientific motivations to understand and reduce uncertainty. We also ask *how* the science and applications communities are presently characterizing uncertainty (Section 3) and how the myriad uncertainties can be distilled into a discrete set of quantitative hydrologic storylines (Section 4). Our broader goal is to critique the current research path, and provide suggestions on ways to move the community forward in fruitful directions (summarized in Section 5). Our focus is on resolving uncertainties that are tractable through improved models and experimental design, as distinct from the uncertainties that hinge on unknowable human decision processes.

2 Societal and scientific motivations to characterize and understand uncertainty

2.1 Societal motivations

The high sensitivity of water resource systems to climate variability creates strong societal motivations to characterize and understand the uncertainty in the weather, climate and hydrologic impacts of global warming. The United Nations *Hyogo Framework for Action*[1] and the World Meteorological Organisation *Global Framework for Climate Services* (GFCS)[2] recognise the central role played by climate information in water resources planning and management, as well as in reducing the risk of disasters associated with floods and droughts. The GFCS calls for research into fundamental climate processes, and into climate impacts on people and sectors over seasonal to multi-decadal timescales. Improving the effective use and communication of uncertain projections are seen as central to enhanced decision-making and more urgent action in the face of climate risks [Moser and Dilling 2004; Pidgeon and Fischhoff 2011; Pathak et al. 2015]. The effective use of uncertain climate information requires a close working relationship between the providers and recipients of climate services, as well as managing user expectations about scientific capabilities through more explicit statements about uncertainty in climate service products [Climate-Services-Partnership 2014].

[1] http://www.unisdr.org/we/coordinate/hfa
[2] http://gfcs.wmo.int/water

Uncertainty about future projections is motivating a revamping of the decision rules and evaluation principles used for water infrastructure projects [Stakhiv 2011; Brown et al. 2012; Yates et al. 2015]. New approaches to water resources planning and management can involve moving away from the traditional search for "optimal" schemes, towards defining solutions that are better suited to "satisficing" across a range of plausible yet uncertain quantitative hydrologic storylines that integrate science and policy explicitly. The SDM framework [e.g., Gregory et al. 2012] encompasses a very broad set of methods rather than prescribing a rigid approach for problem solving. The SDM objective therefore is to arrive at a solution that is robust and meets a given problem's objectives by explicitly considering both uncertainty and institutional setting. Within the construct of the SDM framework, a group of methods have been developed to address uncertainty, and two-widely used techniques for robustness analysis are robust decision-making and information gap analysis [Lempert 2003; Ben-Haim 2006; Hall et al. 2012]. The underlying premise of these so-called robustness analysis techniques under uncertainty is not solely about predicting-then-acting but rather more generally to emphasize the evaluation of the performance of different options within the context of declared uncertainties and the minimization of potential regrets [Lempert et al. 2004].

A renewed interest for research on uncertainty has stimulated the development of new tools to support the "stress-testing" of options, taking into account plausible ranges of climate variability and change [Nazemi et al. 2013; Steinschneider and Brown 2013; Wilby et al. 2014]. However, there remains a need for practical guidance on defining the ranges of uncertainty used to bound stress-test experiments, especially characterizing uncertainties that have hitherto been neglected, and on the opportunities to reduce uncertainties through better methods and models (See Section 3). Further research is also needed to assist decision-makers in the timing of options within dynamic adaptation pathways approaches and in reconciling trade-offs between competing water uses when these all operate under uncertainty [Poff et al. 2015].

2.2 Scientific motivations

A key scientific motivation for research on uncertainty is the quest to understand Earth System change. In part this involves characterizing the uncertainties in model simulations in order to focus research efforts that seek to improve process understanding and predictive models. For example, large uncertainties linked to simplified representations of clouds and precipitation have stimulated new capabilities for "cloud resolving" simulations of regional climate, which in turn have deepened our understanding of how large-scale changes in climate can affect orographic precipitation

[Rasmussen et al. 2014] and the intensity of summer convective storms [Kendon et al. 2014]. In this context uncertainty characterization is necessary to separate climate "signal" from "noise", i.e., to identify changes where we have some confidence, such as declining snowpack [Mote et al. 2005]. Additional research to characterize climate and hydrologic modeling uncertainty will strengthen the scientific foundation for specifying national and international policy actions aimed at mitigating climate change.

3 Embracing uncertainty: Research to reveal and reduce modeling uncertainty

The process of defining quantitative hydrologic storylines of climate change impacts for the water sector has been an active area of research for nearly two decades [Hamlet and Lettenmaier 1999; Christensen et al. 2004; Wilby and Harris 2006; Brekke et al. 2009; Davie et al. 2013; Yates et al. 2015]. Recent research is beginning to reveal how different methodological choices can impact portrayals of climate risk [Bastola et al. 2011; Poulin et al. 2011; Harding et al. 2012; Miller et al. 2012; Velázquez et al. 2013; Addor et al. 2014; Gutmann et al. 2014; Vano et al. 2014; Mendoza et al. 2015]. Quantitative hydrologic storylines of climate change impacts for the water sector must encompass, as much as possible, the full suite of uncertainties associated with (1) global climate modeling, including both model uncertainty and unforced climate variability; (2) regional climate downscaling; and (3) hydrologic modeling. Although not discussed here, such storylines should also reflect indirect consequences of climate variability and change (including hydrologic responses mediated by changes e.g., in land use or atmospheric chemistry such as dust and aerosols) as well as pertinent non-geophysical factors (such as the operational regimes of water infrastructure).

The approach we advocate here is illustrated schematically in Figure 1, following three main steps. First, it is important to adequately characterize uncertainty in all elements of the climate impacts modelling chain, including uncertainty in emissions scenarios, uncertainty in selection and configuration of climate models, uncertainties in internal climate system variability (characterized by small perturbations in climate model initial conditions), uncertainty in climate downscaling, uncertainty associated with the selection and configuration of hydrologic models, and uncertainty in hydrologic model calibration. Many of these uncertainty sources are neglected in climate impact studies. Second, it is important to reduce uncertainties, though selection of likely emission scenarios, informed sampling of climate models (e.g., model culling), sampling of internal climate system variability, restriction to more reliable climate downscaling methods, selection of hydrologic models with adequate process representation, and estimating parameters in hydrologic models using multivariate/multiobjective methods that ensure high model process fidelity, not just high Nash-Sutcliffe efficiencies. Third, from a practical perspective, it is important to construct a small set of example quantitative hydrologic "storylines" of climate change impacts, to provide end-users of climate information with a manageable set of scenarios they can use in their planning studies. The storylines proposed here are more specific than the general climate change narratives proposed by Yates et al. [2015], as the focus is on explicitly characterizing all sources of uncertainty in the modelling process. The following sections will describe the construction of quantitative hydrologic storylines in more detail, focusing on the research that is needed to characterize and reduce uncertainties at various points in the climate impacts modelling chain.

3.1 Global climate modeling

Advances in global climate modeling are yielding more detailed representations of Earth System processes and feedbacks. The specific decisions made when building climate models (often equally plausible and equally defensible modeling strategies), along with the chaotic evolution of climate system states, means that increases in model complexity are often accompanied by increases in the diversity of simulations of future climate [Knutti and Sedláček 2013]. Such diversity in climate model simulations is a positive attribute, as output from multiple models provides the starting point to define alternative climate change storylines that have value for evaluating water sector options [Brekke et al. 2009; Prudhomme et al. 2010; Brown and Wilby 2012].

It is difficult to characterize uncertainties in climate model simulations from the available multiple global climate model ensemble. This is because uncertainties in climate modeling are not explicitly encapsulated in the differences among the climate models that are available for impact assessments [Murphy et al. 2004; Stainforth et al. 2005; Knutti et al. 2010]. As such, the available ensembles do not span the range of possible physical representations, and they conflate modelling error with natural, chaotic, variability. Consequently, climate models offer at best a biased and incomplete sample of the range of possible climate futures [Boberg and Christensen 2012]. Moreover, global climate models may not properly represent natural, unforced climate variability, which can introduce substantial uncertainty in assessments of climate changes on decadal to multi-decadal time scales [Deser et al. 2012a; Deser et al. 2012b]. One solution is to improve the estimation of each model's forced climate signal by using sufficiently large ensembles from single-physics climate model implementations that differ only in their initial conditions [Kay et al. 2014], a practice that may prove computationally impractical for many modelling groups. Another solution is to generate perturbed-physics ensembles [Murphy et al. 2004], though this is also costly as well as logistically difficult to apply across multiple models in a consistent and coordinated way.

Another challenge is to reduce uncertainties in global climate model simulations. As noted above, collective increases in model complexity can actually increase model diversity because different modeling groups make various model development decisions that ultimately impact model simulations. Nevertheless, it is reasonable to accept that all models are not created equal (i.e., some are better than others [Knutti 2010] for a given objective), engendering an opportunity for methods to cull or down-weight models. At present, attempts to do so typically employ criteria based on historical model performance which ostensibly reflect the adequacy of model representations of Earth System processes [Wilby 2010]. For instance, the ability to balance evaporation with precipitation at global scales might be regarded as a fundamental test of a climate model's fitness for hydrological applications [Liepert and Previdi 2012]. Clearly, however, such test metrics must be multi-faceted, which leads inevitably to the further challenge of defining and agreeing upon criteria for model assessment – a problem likely to be viewed variously from different societal and scientific perspectives. For example, the ability to represent important features of the climate system such as the El Nino Southern Oscillation (ENSO), the Madden-Julian Oscillation (MJO) or the Pacific Decadal Oscillation (PDO) might be viewed as key metrics for the evaluation of any climate model regardless of the proposed application. A vexing gap in the model weighting effort, however, has been the dearth of accepted criteria to rate a model's representation of earth system sensitivities to emissions forcing – that is, the model's ability to provide an accurate answer to central questions about future earth system impacts given climate change. Nonetheless, reducing uncertainty through the selection/rejection of climate models is an active area of research, and many groups are experimenting with alternative methods to combine output from multiple climate models [Christensen et al. 2010; Knutti et al. 2010; Mote et al. 2011; Bishop and Abramowitz 2013; Evans et al. 2013]. As the community moves to higher resolution models, it will be interesting to see how explicitly resolving processes (e.g., convection, flow over mountain ranges) changes the profile of inter-model differences.

3.2 Climate downscaling

Advances in regional climate downscaling have been somewhat mixed. The key advances in statistical downscaling were made over two decades ago, with recent work focused primarily on refining traditional methods (see the reviews of Fowler et al. [2007]; Wilby and Fowler [2010]). Non-stationarity in statistical downscaling model parameters is widely recognised as a key problem, but has yet to be seriously characterised or resolved by the community, creating considerable uncertainty in how climate change is portrayed. One approach is to use very high resolution regional climate models as "virtual worlds" to explore the stationarity of predictor-predictand relationships (following the seminal work of Charles et al. [1999]). In contrast to statistical downscaling, dynamical downscaling capabilities have evolved considerably. Such advances are spurred in part by advances in computing, and in part by advances in physics parameterizations [Rasmussen et al. 2014], though characterizing uncertainty in dynamical downscaling remains challenging [Mearns et al. 2013; Done et al. 2014]. The age-old quest to characterize and reduce uncertainties is accentuated by the gap between science and applications, prompting Fowler and Wilby [2007] to call for more thinking about the transposition of insights about downscaling uncertainties into adaptation practice.

Recent research on regional climate downscaling has revealed a number of uncertainties that have hitherto been largely neglected by the water management community. Considering parsimonious statistical models, Gutmann et al. [2014] conducted a comprehensive assessment of the climate model re-scaling methods commonly used by the water management community in the USA, revealing substantial biases, inadequate representation of extremes, and inadequate representation of the spatial scaling characteristics that are important for hydrology. The work suggests that techniques that statistically re-scale the global model change signals are undermined by methodological artefacts that compromise their utility for planning studies. Considering complex dynamical models, Mearns et al. [2013] evaluate the results from the coarse-resolution North American Regional Climate Change Assessment Program (NARCCAP) and reveal that many regional climate model simulations have very different climate change signals to the parent global model. The NARCCAP findings call into question the notion that the use of high-resolution physical parameterizations guarantees that a dynamical downscaling will provide a more precise and accurate regional change projection. Because the choices of parameters and physics parameterizations in regional dynamical downscaling models also give rise to significant uncertainty in projected change signals, a computationally tractable method for exploring and understanding these uncertainties is a critical need. The perturbed physics approach is a key effort to characterize climate dynamical downscaling uncertainties [Yang and Arritt 2002; Murphy et al. 2007], and is now being applied using high-resolution intermediate complexity atmospheric models [Gutmann et al. 2016].

The scope for reducing uncertainty in climate downscaling parallels that in global climate modeling: i.e., avoiding, to the extent possible, the use of physically inadequate models and methods. Put simply, it is important to select among a range of downscaling methods based on their historical performance [Teutschbein and Seibert 2012], including their ability to adequately represent extremes, temporal sequencing (e.g., wet spell length), and the spatial scaling characteristics that are important for hydrology [Gutmann et al. 2014]. As noted previously, dynamical downscaling methods have shown substantial improvements when moving to higher resolutions. In particular, when dynamical models reach sufficient resolution that the convective parameterization can be turned off and mountain ranges are properly resolved [e.g., Kendon et al. 2014; Rasmussen et al. 2014; Ban et al. 2015], then there may be more agreement between models. A critical remaining challenge for the community, as noted earlier, is to assess the ability of downscaling methods to represent change in local-to-regional scale climate and hydrology [Racherla et al. 2012]. As with global climate modeling, therefore, the selection of downscaling methods must proceed with caution, to avoid unintended consequences of over-correcting the noise in climate model simulations (e.g., interpreting internal variability as a model bias) and to avoid being overly confident in the change signal from the global models [Ehret et al. 2012; Gutmann et al. 2014].

3.3 Hydrologic modeling

The last decade brought a greater appreciation for how decisions in hydrologic modeling can affect the portrayal of climate change impacts. Wilby [2005] demonstrated that uncertainties associated with the non-uniqueness of model parameters had a large impact on the portrayal of climate change impacts. More recently, others have emphasized the large impacts associated with the choice of hydrologic models [Miller et al. 2012; Vano et al. 2014], with traditional calibration approaches having limited impact in reducing inter-model differences in the portrayal of climate change signals, even for physically motivated models [Mendoza et al. 2015]. The challenges of characterizing and reducing uncertainties are therefore very acute in the hydrologic modelling community.

Specific limitations of existing hydrologic modeling approaches relate to both (1) missing processes; and (2) inadequate model parameters. In terms of resolving dominant processes, many modelling groups follow a mechanistic modelling approach in order to provide increased confidence that results will hold under different climate regimes [Clark et al. 2015b]. However, many climate impact studies are still conducted using simplistic models that are not robust to non-stationarity [Vaze et al. 2010]. For example, models that parameterize potential evapotranspiration as a function of air temperature can exaggerate the hydrologic sensitivity to climate change [Milly and Dunne 2011; Sheffield et al. 2012; Roderick et al. 2014]. Similar issues arise from neglecting processes such as vegetation change, carbon fertilization, and surface water – groundwater interactions [Maxwell and Kollet 2008; Prudhomme et al. 2014]. Even when models are relatively "complete" in terms of their representation of dominant processes, different model formulations lead to very different simulations of hydrologic processes and land-atmosphere feedbacks [Dirmeyer et al. 2006; Clark et al. 2008; Koster et al. 2011; Clark et al. 2015a]. In terms of improving model parameters, for catchment-scale studies there is too often a reliance on a curve-fitting approach to parameter estimation, leading to compensatory model errors and poor representation of dominant hydrologic processes [Kirchner 2006]; similarly, for regional and continental-scale studies there is too often a reliance on a-priori model parameters that also provide a poor representation of dominant processes [Archfield et al. 2016]. There is an interesting interplay here between processes and parameters – while we advocate mechanistic modelling, physically motivated models have hundreds of parameters that are at best ill defined. We do not even know the saturated hydraulic conductivity of the soil to within an order of magnitude, much less the vertical rooting profiles, soil thickness, interception capacity, and so forth. While we can estimate these parameters globally, they are very crude estimates, and the uncertainty in those parameters translates into large uncertainties in the climate change signal. A key research effort is therefore to better characterize hydrologic modelling uncertainties, using modeling frameworks designed to accommodate multiple spatial configurations, multiple process parameterizations, and multiple model parameter values, and explicitly represent the myriad uncertainties in physically motivated models [Clark et al. 2011; Clark et al. 2015c; Clark et al. 2015d].

Opportunities to reduce uncertainty in hydrologic modeling arise from the judicious selection, configuration and calibration of hydrologic models, guided by physical insights about the studied hydrologic system. Concerning selection, research effort is focused on developing models that appropriately represent the dominant hydrologic processes [Clark et al. 2015b], because neglecting processes (e.g., groundwater-surface water interactions) or over-simplifying process representations (e.g., temperature index snow models) leads to unreliable portrayals of climate change impacts [Milly and Dunne 2011; Lofgren et al. 2013]. Concerning model parameters, research effort is focused on implementing diagnostic and multiple objective approaches to parameter estimation to avoid problems associated with compensatory parameter interactions and parameter non-uniqueness [Gupta et al. 2008], and hence reduce model uncertainty by selecting parameter sets that faithfully represent observed hydrologic processes. As just mentioned, estimates of model parameters are especially uncertain for continental-domain hydrologic model applications [Mizukami et al. 2015], and dedicated research effort on such large-domain applications can substantially reduce model uncertainty [Samaniego et al. 2010].

4 Embracing uncertainty: Developing scenarios of hydrologic change for applications

Quantitative hydrologic storylines of climate change impacts for the water sector must, to the extent possible, encompass the full suite of uncertainties associated with global climate modeling, climate downscaling, hydrologic modeling and natural climate variability [Wilby and Harris 2006; Dobler et al. 2012; Davie et al. 2013; Addor et al. 2014; Schewe et al. 2014; Vano et al. 2014; Mendoza et al. 2015]. Recent research has revealed that the water management community has hitherto neglected or underestimated many of the uncertainties in climate change scenarios, in particular, uncertainties associated with internal climate system variability [Deser et al. 2012a; Deser et al. 2012b; Harding et al. 2012] and hydrologic modeling [Vano et al. 2014; Mendoza et al. 2015]. Other work has revealed several issues with commonly used climate downscaling methods, which can hinder portrayals of the hydrologic impact of climate change [Gutmann et al. 2012; Gutmann et al. 2014; Mizukami et al. 2015].

The selection problem represents an important research challenge because of the need to sample from the very large ensemble in an objective fashion. While some progress has been made on this topic [Tebaldi and Knutti 2007; Knutti et al. 2010; Masson and Knutti 2011; Christierson et al. 2012; Knutti et al. 2013; Wilcke and Barring 2016], existing techniques typically focus primarily on one aspect of the problem, be it model *fidelity*[3] [Tebaldi et al. 2005; Rupp et al. 2013], *sensitivity*[4] [Rogelj et al. 2012; Vano and Lettenmaier 2014], or *diversity*[5] [Bishop and Abramowitz 2013; Knutti et al. 2013], with little work on the interplay among these factors [Sanderson et al. 2015; Vano et al. 2015]. Importantly, there is limited understanding on how considerations of fidelity, sensitivity and diversity informs sampling from the hierarchy of models used to evaluate impacts of climate change

[3] *Fidelity* is the extent to which a model faithfully represents observed processes, as measured by comparing historical model simulations to observations. The suite of metrics used to evaluate model fidelity is very important.

[4] *Sensitivity* is the extent to which the model is sensitive to changes in the parameters of the simulation, e.g., the sensitivity of a model to change in boundary forcing.

[5] *Diversity* is the extent to which models differ. Diversity can relate to both the differences in model construction [Knutti et al., 2013] as well as differences in model simulations [Bishop and Abramowitz, 2013].

in the water resources sector, including global climate models, climate downscaling, and hydrologic models.

Moving forward, it is important to create quantitative hydrologic storylines that reflect these myriad uncertainties. Figure 1 illustrates such an approach, emphasizing the research needed to characterize uncertainties, to reduce uncertainties, and to develop hydrologic storylines for specific end-user applications. A key component of this research (not shown here) is also to reflect uncertainties in the management models and other non-climate stresses that play a strong role in defining possible futures and the effectiveness of different water management options.

In this context it is also important to move beyond the direct consequences of changed air temperature (ΔT) and precipitation (ΔP) regimes on water supply, and consider a wide range of indirect hydrological impacts and dynamics implied by ΔT and ΔP that are not captured in traditional climate change assessments. For example, increased aridity may suggest enhanced dust supply and deposition on snow/ice-pack leading to earlier or more rapid melt; changed patterns of biomass accumulation and desiccation could alter wildfire then subsequent flood and landslide hazards; variations in soil moisture and temperatures could favour disease/pest outbreaks and die-back of forest cover; drier/hotter conditions could drive greater demand for outdoor water use in urban areas. Yates et al. [2015] assert that these types of storylines should be used to stress-test water supply systems and adaptation options in more convincing, holistic ways. More generally, the storyline approach opens the way for including non-climatic pressures, which may be of more immediate concern.

5 Concluding remarks

Quantitative storylines of future hydrologic change must encompass the full suite of uncertainties associated with global climate modeling, climate downscaling, hydrologic modeling, and natural climate variability [Wilby and Harris 2006; Davie et al. 2013; Addor et al. 2014; Schewe et al. 2014; Vano et al. 2014; Mendoza et al. 2015], and ultimately this information must be put in a context such that the water resources planning and management community can incorporate uncertain climate information along with expectations of other changes in order to make informed decisions. This paper reviews how uncertainty is encapsulated in simulations of future change throughout the modeling process. We discuss research that reveals uncertainties that have hitherto been neglected (e.g., due to poor models and methods, and internal climate variability). We also point to research that can reduce uncertainties throughout the set of models and methods that are used to understand the climate sensitivity of water resources (reducing uncertainty through model selection/rejection, and focusing science attention on critical and unmet model development needs). Our review is conducted within the context of a paradigm shift in water resources planning, where the focus has moved to a SDM framework that tests the performance of different options within the context of uncertainties [Lempert et al. 2004; Brown et al. 2012; Yates et al. 2015].

Our broader goal is to critique the current research path, and provide suggestions on ways to move the community forward in fruitful directions. Key research priorities include:

- Improved characterization of uncertainty in global climate models, by enhancing development and use of perturbed physics and initial condition ensembles, and additional research on the selection/rejection of climate models;
- Improved characterization of uncertainty in regional climate downscaling, by: (a) enhancing development of perturbed physics approaches (including more extensive use of dynamical models of intermediate complexity); (b) further development of statistical downscaling methods that can represent metrics important for hydrology (spatial scaling characteristics; extremes); and (c) abandoning downscaling methods that have limited merit for hydrologic impact studies;
- Improved characterization of uncertainty in hydrologic modeling, using frameworks designed to accommodate multiple spatial configurations, multiple process parameterizations, and multiple model parameter values; reducing hydrologic model uncertainty through advances in hydrologic process representation (explicitly simulate dominant processes and improving estimates of model parameters, especially for continental-domain applications); and
- Use comprehensive characterizations of uncertainty in global climate modeling, climate downscaling, land-atmosphere feedback processes, and hydrologic modeling to develop quantitative hydrologic “storylines” describing trajectories of hydrologic change that reflect these myriad uncertainties.

Under the backdrop of uncertainty, it is also important to emphasize areas where we have gained new knowledge and understanding in order to provide meaningful guidance for water resources planning and management. In particular, it is important to identify changes in climate and hydrologic processes where we have some confidence, such as declining snowpack, using quantitative concepts such as the emergence of statistically significant signals, or where a number of changes occur in ways that improve signal to noise. With this understanding in hand, it is also important to improve the use and communication of uncertain projections by enhancing the working relationship between the providers and recipients of climate services, as well as managing user expectations about scientific capabilities through more explicit statements about uncertainty in climate service products and where the results are most robust.

We argue here that 21st century water resource planning creates a strong need for more holistic depictions of uncertainty. It is time to move beyond the common ad-hoc approach of defining a limited set of climate change scenarios based on a small collection of models and methods with known problems. Instead, we advocate a more deliberate approach to assessing hydrologic uncertainty under climate change that is, at the same time, counterbalanced by the need for more value-added explicit modeling [Kanamitsu and DeHaan 2011; Racherla et al. 2012]. This creates a need for new tools and techniques for generating local-to-regional climate and hydrology scenarios for vulnerability assessment and adaptation options appraisal [Nazemi and Wheater 2014; Wilby et al. 2014]. Such research into revealing, reducing and representing uncertainties is essential for defining plausible ranges of quantitative hydrologic storylines of climate change impacts to support water resources planning and management.

6 Conflict of interest

On behalf of all authors, the corresponding author states that there is no conflict of interest.

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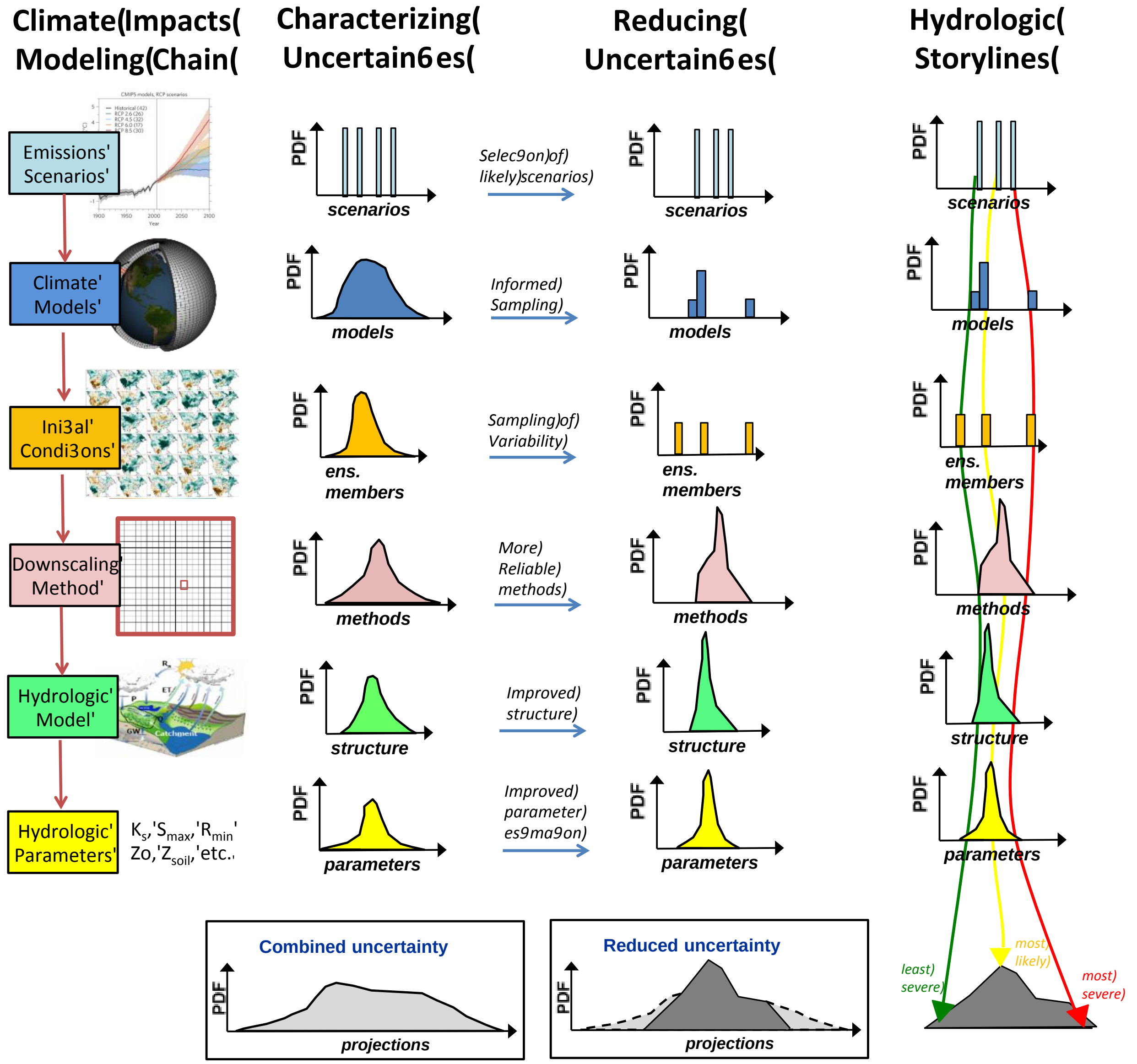

Figure 1. Schematic on approaches to explicitly characterize and reduce the myriad uncertainties in assessments of the hydrologic impacts of climate change, and the development of representative quantitative hydrologic storylines for specific applications.