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# 1 Characterizing uncertainty of the hydrologic impacts of 2 climate change

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12

## 13 **Abstract**

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

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28

## 29 **1 Introduction**

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

42 Developing quantitative hydrologic storylines of future change for the water sector is an  
43 interdisciplinary endeavour – it entails representing current knowledge of global change in the  
44 context of substantial uncertainty in the trajectory of future climate and the associated impacts on  
45 hydrologic processes. Recent research has shown the importance of assessing uncertainty from a  
46 large number of sources (Figure 1; see also Section 3), including, global model structure [Meehl et al.  
47 2005; Knutti and Sedláček 2013], internal climate variability [Deser et al. 2012a; Deser et al. 2012b],  
48 climate downscaling methods [Mearns et al. 2013; Gutmann et al. 2014] and hydrologic models  
49 [Addor et al. 2014; Mendoza et al. 2014; Vano et al. 2014; Mizukami et al. 2015]. Increasing  
50 computational resources permit more sources to be combined, such that model ensemble sizes  
51 have grown from a handful of experiments a few decades ago to hundreds of projections now. This  
52 plethora of available projections and methodological options is outpacing the ability of the  
53 applications community to handle large ensembles and thereby comprehensively characterize  
54 uncertainty [Christierson et al. 2012]. Furthermore, it is critical to keep the application community  
55 engaged and informed to ensure that this plethora of science information can be translated into  
56 actionable water resources planning and operational decisions.

57 This paper provides a critical review of capabilities to characterize and understand uncertainty in  
58 the hydrologic impacts of climate change (excluding changes in water management). We conduct  
59 our review in the context of a paradigm shift in water resources planning, namely a move toward a  
60 structured decision making (SDM) framework that tests the performance of different options that

61 are highlighted within an envelope of broad uncertainty [Lempert et al. 2004; Brown et al. 2012;  
62 Yates et al. 2015]. Specifically, we ask *why* research is needed to characterize uncertainty in climate  
63 change impacts on hydrology (Section 2). We consider societal motivations for appraising the  
64 potential impacts of climate change in water resources planning and management, as well as  
65 scientific motivations to understand and reduce uncertainty. We also ask *how* the science and  
66 applications communities are presently characterizing uncertainty (Section 3) and how the myriad  
67 uncertainties can be distilled into a discrete set of quantitative hydrologic storylines (Section 4).  
68 Our broader goal is to critique the current research path, and provide suggestions on ways to move  
69 the community forward in fruitful directions (summarized in Section 5). Our focus is on resolving  
70 uncertainties that are tractable through improved models and experimental design, as distinct from  
71 the uncertainties that hinge on unknowable human decision processes.

## 72 **2 Societal and scientific motivations to characterize and understand** 73 **uncertainty**

### 74 **2.1 Societal motivations**

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

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<sup>1</sup> <http://www.unisdr.org/we/coordinate/hfa>

<sup>2</sup> <http://gfcs.wmo.int/water>

89 Uncertainty about future projections is motivating a revamping of the decision rules and evaluation  
90 principles used for water infrastructure projects [Stakhiv 2011; Brown et al. 2012; Yates et al.  
91 2015]. New approaches to water resources planning and management can involve moving away  
92 from the traditional search for “optimal” schemes, towards defining solutions that are better suited  
93 to “satisficing” across a range of plausible yet uncertain quantitative hydrologic storylines that  
94 integrate science and policy explicitly. The SDM framework [e.g., Gregory et al. 2012] encompasses  
95 a very broad set of methods rather than prescribing a rigid approach for problem solving. The SDM  
96 objective therefore is to arrive at a solution that is robust and meets a given problem’s objectives by  
97 explicitly considering both uncertainty and institutional setting. Within the construct of the SDM  
98 framework, a group of methods have been developed to address uncertainty, and two-widely used  
99 techniques for robustness analysis are robust decision-making and information gap analysis  
100 [Lempert 2003; Ben-Haim 2006; Hall et al. 2012]. The underlying premise of these so-called  
101 robustness analysis techniques under uncertainty is not solely about predicting-then-acting but  
102 rather more generally to emphasize the evaluation of the performance of different options within  
103 the context of declared uncertainties and the minimization of potential regrets [Lempert et al.  
104 2004].

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

## 114 **2.2 Scientific motivations**

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

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

### 127 **3 Embracing uncertainty: Research to reveal and reduce modeling** 128 **uncertainty**

129 The process of defining quantitative hydrologic storylines of climate change impacts for the water  
130 sector has been an active area of research for nearly two decades [Hamlet and Lettenmaier 1999;  
131 Christensen et al. 2004; Wilby and Harris 2006; Brekke et al. 2009; Davie et al. 2013; Yates et al.  
132 2015]. Recent research is beginning to reveal how different methodological choices can impact  
133 portrayals of climate risk [Bastola et al. 2011; Poulin et al. 2011; Harding et al. 2012; Miller et al.  
134 2012; Velázquez et al. 2013; Addor et al. 2014; Gutmann et al. 2014; Vano et al. 2014; Mendoza et al.  
135 2015]. Quantitative hydrologic storylines of climate change impacts for the water sector must  
136 encompass, as much as possible, the full suite of uncertainties associated with (1) global climate  
137 modeling, including both model uncertainty and unforced climate variability; (2) regional climate  
138 downscaling; and (3) hydrologic modeling. Although not discussed here, such storylines should also  
139 reflect indirect consequences of climate variability and change (including hydrologic responses  
140 mediated by changes e.g., in land use or atmospheric chemistry such as dust and aerosols) as well  
141 as pertinent non-geophysical factors (such as the operational regimes of water infrastructure).

142 The approach we advocate here is illustrated schematically in Figure 1, following three main steps.  
143 First, it is important to adequately characterize uncertainty in all elements of the climate impacts  
144 modelling chain, including uncertainty in emissions scenarios, uncertainty in selection and  
145 configuration of climate models, uncertainties in internal climate system variability (characterized  
146 by small perturbations in climate model initial conditions), uncertainty in climate downscaling,  
147 uncertainty associated with the selection and configuration of hydrologic models, and uncertainty  
148 in hydrologic model calibration. Many of these uncertainty sources are neglected in climate impact  
149 studies. Second, it is important to reduce uncertainties, though selection of likely emission  
150 scenarios, informed sampling of climate models (e.g., model culling), sampling of internal climate  
151 system variability, restriction to more reliable climate downscaling methods, selection of

152 hydrologic models with adequate process representation, and estimating parameters in hydrologic  
153 models using multivariate/multiobjective methods that ensure high model process fidelity, not just  
154 high Nash-Sutcliffe efficiencies. Third, from a practical perspective, it is important to construct a  
155 small set of example quantitative hydrologic “storylines” of climate change impacts, to provide end-  
156 users of climate information with a manageable set of scenarios they can use in their planning  
157 studies. The storylines proposed here are more specific than the general climate change narratives  
158 proposed by Yates et al. [2015], as the focus is on explicitly characterizing all sources of uncertainty  
159 in the modelling process. The following sections will describe the construction of quantitative  
160 hydrologic storylines in more detail, focusing on the research that is needed to characterize and  
161 reduce uncertainties at various points in the climate impacts modelling chain.

### 162 **3.1 Global climate modeling**

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

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

184 perturbed-physics ensembles [Murphy et al. 2004], though this is also costly as well as logistically  
185 difficult to apply across multiple models in a consistent and coordinated way.

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

### 211 **3.2 Climate downscaling**

212 Advances in regional climate downscaling have been somewhat mixed. The key advances in  
213 statistical downscaling were made over two decades ago, with recent work focused primarily on  
214 refining traditional methods (see the reviews of Fowler et al. [2007]; Wilby and Fowler [2010]).  
215 Non-stationarity in statistical downscaling model parameters is widely recognised as a key problem,



216 but has yet to be seriously characterised or resolved by the community, creating considerable  
217 uncertainty in how climate change is portrayed. One approach is to use very high resolution  
218 regional climate models as “virtual worlds” to explore the stationarity of predictor-predictand  
219 relationships (following the seminal work of Charles et al. [1999]). In contrast to statistical  
220 downscaling, dynamical downscaling capabilities have evolved considerably. Such advances are  
221 spurred in part by advances in computing, and in part by advances in physics parameterizations  
222 [Rasmussen et al. 2014], though characterizing uncertainty in dynamical downscaling remains  
223 challenging [Mearns et al. 2013; Done et al. 2014]. The age-old quest to characterize and reduce  
224 uncertainties is accentuated by the gap between science and applications, prompting Fowler and  
225 Wilby [2007] to call for more thinking about the transposition of insights about downscaling  
226 uncertainties into adaptation practice.

227 Recent research on regional climate downscaling has revealed a number of uncertainties that have  
228 hitherto been largely neglected by the water management community. Considering parsimonious  
229 statistical models, Gutmann et al. [2014] conducted a comprehensive assessment of the climate  
230 model re-scaling methods commonly used by the water management community in the USA,  
231 revealing substantial biases, inadequate representation of extremes, and inadequate representation  
232 of the spatial scaling characteristics that are important for hydrology. The work suggests that  
233 techniques that statistically re-scale the global model change signals are undermined by  
234 methodological artefacts that compromise their utility for planning studies. Considering complex  
235 dynamical models, Mearns et al. [2013] evaluate the results from the coarse-resolution North  
236 American Regional Climate Change Assessment Program (NARCCAP) and reveal that many regional  
237 climate model simulations have very different climate change signals to the parent global model.  
238 The NARCCAP findings call into question the notion that the use of high-resolution physical  
239 parameterizations guarantees that a dynamical downscaling will provide a more precise and  
240 accurate regional change projection. Because the choices of parameters and physics  
241 parameterizations in regional dynamical downscaling models also give rise to significant  
242 uncertainty in projected change signals, a computationally tractable method for exploring and  
243 understanding these uncertainties is a critical need. The perturbed physics approach is a key effort  
244 to characterize climate dynamical downscaling uncertainties [Yang and Arritt 2002; Murphy et al.  
245 2007], and is now being applied using high-resolution intermediate complexity atmospheric  
246 models [Gutmann et al. 2016].

247 The scope for reducing uncertainty in climate downscaling parallels that in global climate modeling;  
248 i.e., avoiding, to the extent possible, the use of physically inadequate models and methods. Put  
249 simply, it is important to select among a range of downscaling methods based on their historical  
250 performance [Teutschbein and Seibert 2012], including their ability to adequately represent  
251 extremes, temporal sequencing (e.g., wet spell length), and the spatial scaling characteristics that  
252 are important for hydrology [Gutmann et al. 2014]. As noted previously, dynamical downscaling  
253 methods have shown substantial improvements when moving to higher resolutions. In particular,  
254 when dynamical models reach sufficient resolution that the convective parameterization can be  
255 turned off and mountain ranges are properly resolved [e.g., Kendon et al. 2014; Rasmussen et al.  
256 2014; Ban et al. 2015], then there may be more agreement between models. A critical remaining  
257 challenge for the community, as noted earlier, is to assess the ability of downscaling methods to  
258 represent change in local-to-regional scale climate and hydrology [Racherla et al. 2012]. As with  
259 global climate modeling, therefore, the selection of downscaling methods must proceed with  
260 caution, to avoid unintended consequences of over-correcting the noise in climate model  
261 simulations (e.g., interpreting internal variability as a model bias) and to avoid being overly  
262 confident in the change signal from the global models [Ehret et al. 2012; Gutmann et al. 2014].

### 263 **3.3 Hydrologic modeling**

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

273 Specific limitations of existing hydrologic modeling approaches relate to both (1) missing processes;  
274 and (2) inadequate model parameters. In terms of resolving dominant processes, many modelling  
275 groups follow a mechanistic modelling approach in order to provide increased confidence that  
276 results will hold under different climate regimes [Clark et al. 2015b]. However, many climate  
277 impact studies are still conducted using simplistic models that are not robust to non-stationarity  
278 [Vaze et al. 2010]. For example, models that parameterize potential evapotranspiration as a

279 function of air temperature can exaggerate the hydrologic sensitivity to climate change [Milly and  
280 Dunne 2011; Sheffield et al. 2012; Roderick et al. 2014]. Similar issues arise from neglecting  
281 processes such as vegetation change, carbon fertilization, and surface water – groundwater  
282 interactions [Maxwell and Kollet 2008; Prudhomme et al. 2014]. Even when models are relatively  
283 “complete” in terms of their representation of dominant processes, different model formulations  
284 lead to very different simulations of hydrologic processes and land-atmosphere feedbacks  
285 [Dirmeyer et al. 2006; Clark et al. 2008; Koster et al. 2011; Clark et al. 2015a]. In terms of improving  
286 model parameters, for catchment-scale studies there is too often a reliance on a curve-fitting  
287 approach to parameter estimation, leading to compensatory model errors and poor representation  
288 of dominant hydrologic processes [Kirchner 2006]; similarly, for regional and continental-scale  
289 studies there is too often a reliance on a-priori model parameters that also provide a poor  
290 representation of dominant processes [Archfield et al. 2016]. There is an interesting interplay here  
291 between processes and parameters – while we advocate mechanistic modelling, physically  
292 motivated models have hundreds of parameters that are at best ill defined. We do not even know  
293 the saturated hydraulic conductivity of the soil to within an order of magnitude, much less the  
294 vertical rooting profiles, soil thickness, interception capacity, and so forth. While we can estimate  
295 these parameters globally, they are very crude estimates, and the uncertainty in those parameters  
296 translates into large uncertainties in the climate change signal. A key research effort is therefore to  
297 better characterize hydrologic modelling uncertainties, using modeling frameworks designed to  
298 accommodate multiple spatial configurations, multiple process parameterizations, and multiple  
299 model parameter values, and explicitly represent the myriad uncertainties in physically motivated  
300 models [Clark et al. 2011; Clark et al. 2015c; Clark et al. 2015d].

301 Opportunities to reduce uncertainty in hydrologic modeling arise from the judicious selection,  
302 configuration and calibration of hydrologic models, guided by physical insights about the studied  
303 hydrologic system. Concerning selection, research effort is focused on developing models that  
304 appropriately represent the dominant hydrologic processes [Clark et al. 2015b], because neglecting  
305 processes (e.g., groundwater-surface water interactions) or over-simplifying process  
306 representations (e.g., temperature index snow models) leads to unreliable portrayals of climate  
307 change impacts [Milly and Dunne 2011; Lofgren et al. 2013]. Concerning model parameters,  
308 research effort is focused on implementing diagnostic and multiple objective approaches to  
309 parameter estimation to avoid problems associated with compensatory parameter interactions and  
310 parameter non-uniqueness [Gupta et al. 2008], and hence reduce model uncertainty by selecting  
311 parameter sets that faithfully represent observed hydrologic processes. As just mentioned,

312 estimates of model parameters are especially uncertain for continental-domain hydrologic model  
313 applications [Mizukami et al. 2015], and dedicated research effort on such large-domain  
314 applications can substantially reduce model uncertainty [Samaniego et al. 2010].

## 315 **4 Embracing uncertainty: Developing scenarios of hydrologic change** 316 **for applications**

317 Quantitative hydrologic storylines of climate change impacts for the water sector must, to the  
318 extent possible, encompass the full suite of uncertainties associated with global climate modeling,  
319 climate downscaling, hydrologic modeling and natural climate variability [Wilby and Harris 2006;  
320 Dobler et al. 2012; Davie et al. 2013; Addor et al. 2014; Schewe et al. 2014; Vano et al. 2014;  
321 Mendoza et al. 2015]. Recent research has revealed that the water management community has  
322 hitherto neglected or underestimated many of the uncertainties in climate change scenarios, in  
323 particular, uncertainties associated with internal climate system variability [Deser et al. 2012a;  
324 Deser et al. 2012b; Harding et al. 2012] and hydrologic modeling [Vano et al. 2014; Mendoza et al.  
325 2015]. Other work has revealed several issues with commonly used climate downscaling methods,  
326 which can hinder portrayals of the hydrologic impact of climate change [Gutmann et al. 2012;  
327 Gutmann et al. 2014; Mizukami et al. 2015].

328 The selection problem represents an important research challenge because of the need to sample  
329 from the very large ensemble in an objective fashion. While some progress has been made on this  
330 topic [Tebaldi and Knutti 2007; Knutti et al. 2010; Masson and Knutti 2011; Christerson et al. 2012;  
331 Knutti et al. 2013; Wilcke and Barring 2016], existing techniques typically focus primarily on one  
332 aspect of the problem, be it model *fidelity*<sup>3</sup> [Tebaldi et al. 2005; Rupp et al. 2013], *sensitivity*<sup>4</sup> [Rogelj  
333 et al. 2012; Vano and Lettenmaier 2014], or *diversity*<sup>5</sup> [Bishop and Abramowitz 2013; Knutti et al.  
334 2013], with little work on the interplay among these factors [Sanderson et al. 2015; Vano et al.  
335 2015]. Importantly, there is limited understanding on how considerations of fidelity, sensitivity and  
336 diversity informs sampling from the hierarchy of models used to evaluate impacts of climate change

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<sup>3</sup> *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.

<sup>4</sup> *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.

<sup>5</sup> *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].

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

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

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

## 357 **5 Concluding remarks**

358 Quantitative storylines of future hydrologic change must encompass the full suite of uncertainties  
359 associated with global climate modeling, climate downscaling, hydrologic modeling, and natural  
360 climate variability [Wilby and Harris 2006; Davie et al. 2013; Addor et al. 2014; Schewe et al. 2014;  
361 Vano et al. 2014; Mendoza et al. 2015], and ultimately this information must be put in a context  
362 such that the water resources planning and management community can incorporate uncertain  
363 climate information along with expectations of other changes in order to make informed decisions.  
364 This paper reviews how uncertainty is encapsulated in simulations of future change throughout the  
365 modeling process. We discuss research that reveals uncertainties that have hitherto been neglected  
366 (e.g., due to poor models and methods, and internal climate variability). We also point to research  
367 that can reduce uncertainties throughout the set of models and methods that are used to

368 understand the climate sensitivity of water resources (reducing uncertainty through model  
369 selection/rejection, and focusing science attention on critical and unmet model development  
370 needs). Our review is conducted within the context of a paradigm shift in water resources planning,  
371 where the focus has moved to a SDM framework that tests the performance of different options  
372 within the context of uncertainties [Lempert et al. 2004; Brown et al. 2012; Yates et al. 2015].

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

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

394 Under the backdrop of uncertainty, it is also important to emphasize areas where we have gained  
395 new knowledge and understanding in order to provide meaningful guidance for water resources  
396 planning and management. In particular, it is important to identify changes in climate and  
397 hydrologic processes where we have some confidence, such as declining snowpack, using  
398 quantitative concepts such as the emergence of statistically significant signals, or where a number  
399 of changes occur in ways that improve signal to noise. With this understanding in hand, it is also

400 important to improve the use and communication of uncertain projections by enhancing the  
401 working relationship between the providers and recipients of climate services, as well as managing  
402 user expectations about scientific capabilities through more explicit statements about uncertainty  
403 in climate service products and where the results are most robust.

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

## 415 **6 Conflict of interest**

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

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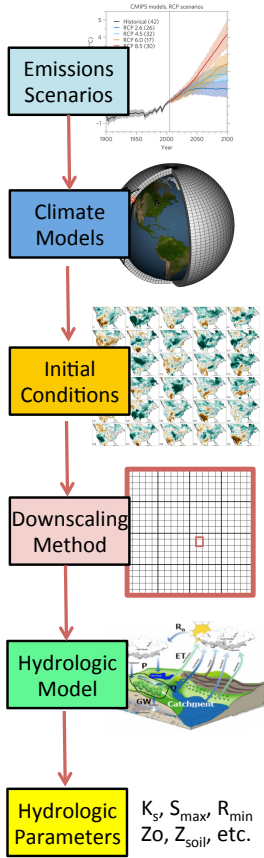
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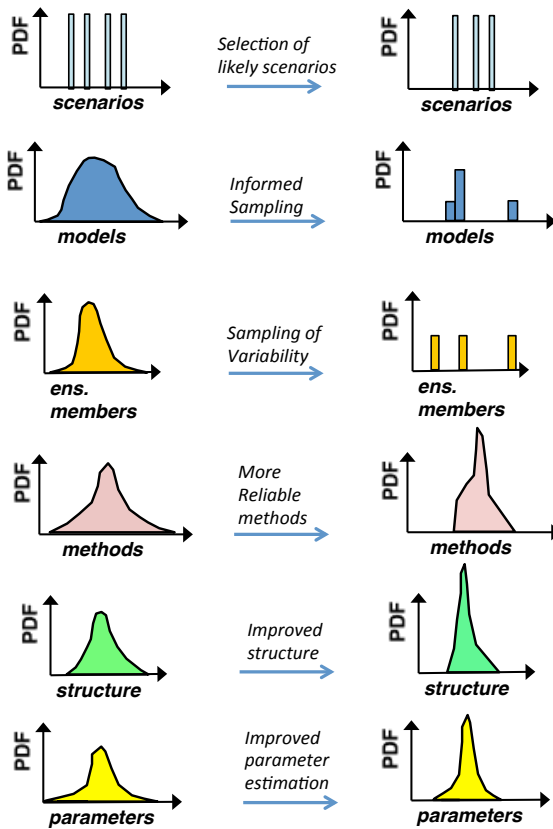
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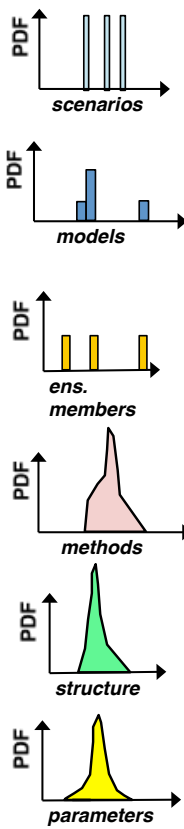
### Climate Impacts Modeling Chain



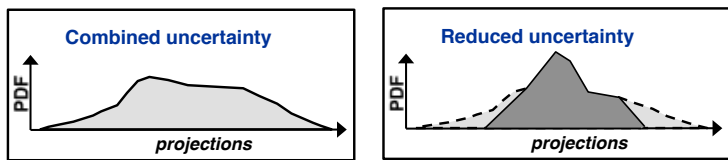
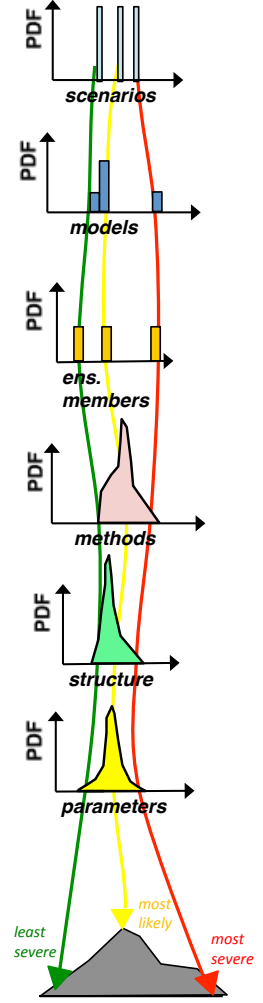
### Characterizing Uncertainties



### Reducing Uncertainties



### Hydrologic Storylines



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