US CLIVAR
Climate Variability & Predictability

VARIATIONS

doi:10.5065/D62N513R

Summer 2018 • Vol. 16, No. 3

Uncertainty in climate projections

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"Scientific knowledge is a body of statements of varying degrees of uncertainty, some of them unsure; some of them are nearly sure; but none is absolutely certain." – Richard Feynman

Science informs and empowers. Uncertainty is an inherent part of science and is fundamental to scientific progress. It can propagate through multiple ways in the knowledge generation and dissemination process. Uncertainty can be classified on the basis of its nature (i.e., uncertainty due to imperfection in our knowledge, or the underlying cause of how the uncertainty came to exist), location (i.e., origin of uncertainty in the model outcome), and level (i.e., degree of uncertainty along the spectrum of total determinism to total ignorance). Uncertainty can be assessed, quantified, and constrained through different processes, and in some cases, it can be reduced. To inform sound public choices, and provide accurate and actionable information for decision making, it is important to acknowledge and communicate uncertainties in scientific knowledge.

Climate uncertainty and risk

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Research scientists focus on the knowledge frontier, where doubt and uncertainty are inherent. Formal uncertainty quantification of computer models is less relevant to science than an assessment of whether the model helps us learn about how the system works.

However in context of the science-policy interface, uncertainty matters. There is a growing need for more constructive approaches to accountability about the different dimensions of uncertainty in climate change as related to policy making (e.g., Smith and Stern 2011) — what may happen in the future and what actions might be appropriate now.

Risk is the probability that some undesirable event will occur and often described as the combination of that probability and the corresponding consequence of the event. Economists have a specific definition of risk and uncertainty that harkens back to Knight (1921). Knightian risk denotes the calculable and thus controllable part of what is unknowable, implying that robust probability information is available about future outcomes. Knightian uncertainty addresses what is incalculable and uncontrollable.

IN THIS ISSUE

This article on climate uncertainty and risk integrates perspectives from climate modeling, philosophy of science and decision making under uncertainty, extending previous analyses by the author (Curry and Webster 2011; Curry 2011). The objective is to explore the kinds of evidence and reasoning that can help inform decision makers as to whether and how they should use climate models for different applications.

Characterizing uncertainty

There are numerous categorizations and hierarchies of risk and uncertainty, which are further complicated by different disciplines using terms in different ways (for a summary, see Spiegelhaler and Rausch 2011). The categorization presented here focuses on model predictions for an intrinsically probabilistic system. This categorization discriminates among two dimensions of uncertainty (Walker et al, 2013; Kwakkel et al. 2010): location and level of uncertainty.

The *location* of uncertainty refers to where the uncertainty manifests itself within the model complex:

- *Framing and context:* identifies the boundaries of the modeled system. Portions of the real world that are outside the modeled system leave an invisible range of other uncertainties.
- *Model structure uncertainty:* uncertainty about the conceptual modeling of the physical system, including the selection of subsystems to include, often introduced as a pragmatic compromise given limited computational resources.
- *Model technical uncertainty:* the implementation of the model solution on a computer, including solution approximation and numerical errors.
- *Input uncertainty:* relates to uncertainty in model inputs that describe the system and the external forces that drive system changes.
- *Parameter uncertainty:* uncertain constants and other parameters that are largely contained in subgrid scale parameterizations.
- *Model outcome uncertainty:* the propagation of the aforementioned uncertainties through the model simulation.
- *Uncertainty quantification error:* due to Monte Carlo sampling used for probabilities and in the error quantification procedure itself.

The *level* of uncertainty relates to where the model outcome uncertainty ranks in the spectrum between complete certainty and total ignorance:

- *Complete certainty:* deterministic knowledge; no uncertainty.
- *Statistical uncertainty* (Knightian risk): outcomes can never be known precisely, but precise, decision-relevant probability statements can be provided.

This issue of *Variations* is a collection of articles on various aspects of uncertainties in climate projections. In her essay, Curry integrates perspectives from climate modeling, philosophy of science, and decision making under uncertainty to examine when and how climate modeling can be used for decision-making applications. Wootten discusses uncertainties in statistical downscaling and concludes with some future research directions. Articles by Chueng and by Fei and McCarl explore ways in which uncertainties can be characterized to inform fisheries management and adaptation planning for agriculture, respectively. Morss and others highlight a project that integrates research on decadal prediction and communication of associated uncertainty for use in decision making. These articles shed light on some ways in which uncertainties in climate projections can be assessed, managed, and communicated.

The advancement of our society is closely coupled to the scientific and technological discoveries that transform knowledge. Helping people understand the value of science is a first step and making sure that those same people recognize that uncertainty does not undermine the inherent value of scientific information, but rather is part of that information, is the second.

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- *Scenario uncertainty* (ambiguity): a range of plausible outcomes (scenarios) are enumerated but with a weak basis for ranking them in terms of likelihood.
- *Deep uncertainty* (recognized ignorance)*:* the scientific basis for developing outcomes (scenarios) is weak; future outcomes lie outside of the realm of regular or quantifiable expectations.
- *Total ignorance:* the deepest level of uncertainty, to the extent that we do not even know that we do not know.

If the policy-making challenge is defined in context of the response of climate to future greenhouse gas emissions, the uncertainty level is characterized as "scenario uncertainty." In this context, scenario uncertainty arises not only from uncertainty in future emissions but also from uncertainty in the equilibrium climate sensitivity (ECS) to CO_2. According to the Intergovernmental Panel on Climate Change (IPCC) Fifth Assessment Report (AR5; IPCC 2013), "there is *high confidence* that *ECS* is *extremely unlikely* less than 1°C and *medium confidence* that the ECS is *likely* between 1.5°C and 4.5°C and *very unlikely* greater than 6°C." The AR5 further states "No best estimate for equilibrium climate sensitivity can now be given because of a lack of agreement on values across assessed lines of evidence and studies." Despite the fact that we know a range of values within which the ECS is very likely to fall, we do not have grounds for associating a specific probability distribution with ECS.

If the policy-making challenge is defined in the context of the actual evolution of the 21st century climate (such as for vulnerability and impact assessments), then the uncertainty level increases to deep uncertainty. Apart from the issue of unknown future greenhouse gas emissions, we have very little basis for developing future scenarios of solar variation, volcanic eruptions and long-term internal variability. The likelihood of unanticipated outcomes (surprises) needs to be acknowledged.

Epistemology of climate models

The IPCC Fourth Assessment Report provided the following conclusion about climate models:

> *"There is considerable confidence that climate models provide credible quantitative estimates of future climate change, particularly at continental scales and above." (Randall et al. 2007, p. 600)*

Is this level of confidence in climate model projections justified? Given the complexity of the Earth climate system, the foundational basis for the knowledge claims made based on global climate models deserves greater attention (Loehle 2018).

Climate models have been evaluated (e.g. Flato et al. 2013) by assessing how well model results fit observation-based data (empirical accuracy) and how well they agree with other models or model versions (robustness). Parker (2011) has argued that robustness does not objectively increase confidence in simulations of future climate change. Baumberger et al. (2017) address the challenge of building confidence in future climate model predictions through a combination of empirical accuracy, robustness and coherence with background knowledge. Assessing coherence with background knowledge is limited because of empirical parameterizations and the epistemic opacity of complex models (Lenhard and Winsberg 2010).

With regards to empirical adequacy, the climate modeling community is beginning to apply uncertainty quantification (UQ) concepts to climate models (Qian et al. 2016). These endeavors are focused on exploring parameter uncertainty (towards optimizing model parameter selection) and on evaluating prediction error. Additional efforts are identifying which model variables to focus on in prediction error analyses (Burrows 2018) and evaluating models at shorter weather timescales and process levels.

A broader perspective on this issue is provided by recent scholarship on the epistemology of simulation, including how simulation models are confirmed. Lloyd (2009) describes how observational data are used in the evaluation of climate models and suggests new ways of viewing the significance of these model-data comparisons. However, attempts to assess climate model adequacy and similarity to the observed climate through demonstrating empirical accuracy are fraught with challenges: inadequacy of data, selection of variables to confirm and on which time and space scales, a vast and multi-dimensional parameter space to be explored, model initialization and internal variability, and concerns about circularity with regards to data used in both model tuning and confirmation.

Parker (2009) suggests that known climate model error is too pervasive to allow climate model confirmation to be of use. Parker proposes a shift in approach from confirming climate models to confirming their "adequacy for purpose." Adequacy-for-purpose assessments involve estimating what the degrees of accuracy of simulations for a wide variety of observed climatic quantities imply about the correctness of uncertain model assumptions and results. Assessing adequacy-for-purpose hypotheses is a daunting task owing to confirmation holism (Lenhard and Winsberg 2010).

Assessing the adequacy of climate models for the purpose of predicting future climate is particularly difficult and arguably impossible. It is often assumed that if climate models reproduce current and past climates reasonably well, then we can have confidence in future predictions. However, empirical accuracy, to a substantial degree, may be due to tuning rather than to the model structural form. Further, the model may lack representations of processes and feedbacks that would significantly influence future climate change. Therefore, reliably reproducing past and present climate is not a sufficient condition for a model to be adequate for long-term projections, particularly for high-forcing scenarios that are well outside those previously observed in the instrumental record.

Given the unaddressed concerns about uncertainties in model structural form and framing, Katzav (2014) argues that useful climate model assessment should aim to demonstrate that the simulations describe real possibilities. A simulation is taken to be a real possibility if its realization is compatible with our background knowledge and that background knowledge does not exclude the realization of the simulated scenario over the target period.

Developing scenarios of climate futures

The possibilistic view regards the spread of an ensemble as a range of outcomes that cannot be ruled out. Stainforth et al. (2007) say, however, that climate models cannot be used to show that some possibilities are not real. Further, owing to structural limitations, existing climate models do not allow exploration of all the theoretical possibilities that are compatible with our knowledge of the basic way the climate system actually behaves. Some of these unexplored possibilities may turn out to be real ones.

Smith and Stern (2011) argue that there is value in scientific speculation on policy-relevant aspects of plausible, high-impact scenarios, even though we can neither model them realistically nor provide a precise estimate of their probability. A surprise occurs if a possibility that had not even been articulated becomes true. Efforts to avoid surprises begin with ensuring there has been a fully imaginative consideration of possible future outcomes.

When background knowledge supports doing so, modifying model results to broaden the range of possibilities they represent can generate additional scenarios. Further, the possibilist view extends to scenarios other than those that are created by global climate models. Simple climate models, process models and data-driven models can also be used as the basis for generating scenarios of future climate. The paleoclimate record provides a rich source of information for developing future scenarios (e.g., Cook et al. 2018). More creative approaches, such as mental simulation and abductive reasoning, also have value (NAS

2018). These alternative methods for generating future climate scenarios are particularly relevant for developing regional scenarios (for which global models are known to be inadequate) and impact variables such as sea level rise (that are not directly simulated by global climate models).

The potential problem of generating a plethora of potentially useless future scenarios is avoided if we focus on scenarios that we expect to be significant in a policy context. Smith and Stern (2011) make an argument for estimating whether a scenario outcome has a less than 1-in-200 chance, which is a threshold that is relevant to financial risk managers.

The worst-case scenario is judged to be the most extreme scenario that cannot be falsified as impossible based upon our background knowledge (Betz 2010). The scientific community involved in predicting future sea level rise has expended considerable effort in articulating the worst-case scenario (e.g., LeBars 2017). Sea level predictions are only indirectly driven by global climate models, since these models do not predict the mass balance of glaciers and ice sheets, land water storage or isostatic adjustments. So estimates of the worst-case scenario integrate climate model simulations, process model simulations, estimates from the literature, and paleoclimatic observations.

Integrated Assessment Models

Optimization Integrated Assessment Models (IAMs) are widely used to assess impacts of climate change and various policy responses (see Frisch 2013 for a summary). For example, to assess the social cost of carbon, IAMs couple an economic general equilibrium model to an extremely simplified climate model. According to expected utility theory, we should adopt the climate policy that maximizes expected utility — the extent to which an outcome is preferable to the alternatives.

The key climate science input to IAMs is the probability density function of equilibrium climate sensitivity (ECS). The dilemma is that with regards to ECS, we are in a situation of scenario (Knightian) uncertainty — we simply do not have grounds for formulating a precise probability distribution. Other deep uncertainties in IAM inputs include the damage function (economic impact) and discount rate (discounting of future utilities with respect to the present). Without precise probability distributions, no expected utility calculation is possible.

This problem has been addressed by creating a precise probability distribution based upon the parameters provided by the IPCC assessment reports (NAS 2017). In effect, IAMs convert Knightian uncertainty in ECS into precise probabilities. Of particular concern is how the upper end of the ECS distribution is treated—typically with a fat tail. The end result is that this most important part of the distribution that drives the economic costs of carbon is based upon a statistically manufactured fat tail that has no scientific justification.

Subjective or imprecise probabilities may be the best ones available. Some decision techniques have been formulated using imprecise probabilities that do not depart too much from the appeal to expected utility (e.g., Troffaes 2007). Frisch (2013) suggests that such applications of IAMs are dangerous, because while they purport to offer precise numbers to use for policy guidance, that precision is illusory and fraught with assumption and value judgments.

Policies optimized for a "likely" future may fail in the face of surprise. At best, policy makers have a range of possible future scenarios to consider. Alternative decision-analytic frameworks that are consistent with conditions of deep uncertainty can make more scientifically defensible use of scenarios of climate futures.

For situations of deep uncertainty, precautionary and robust approaches are appropriate. A precautionary appraisal is initiated when there is uncertainty. A robust policy is defined to be one that yields outcomes that are deemed to be satisfactory across a wide range of plausible future outcomes (e.g., Walker et al. 2016). As such, robust policy making interfaces well with possibilistic approaches that generate a range of possible futures. Flexible strategies are adaptive and can be quickly adjusted to advancing scientific insights and clarification of scenarios of future outcomes.

Conclusions

While climate models continue to be used by climate scientists to increase understanding about how the climate system works, they are also playing a central role in developing international, national, and local policies.

There is a gap between what climate scientists can provide versus the information desired by policy makers. Spiegelhalter and Rausch (2011) state that it is important for scientists to avoid the attrition of uncertainty in the face of an inappropriate demand for certainty from policy makers. Betz (2010) reminds us that the difficulties of the problem must not serve as an excuse for scientists to simplify the epistemic situation, thereby predetermining the complex value judgments involved.

Both climate scientists and policy makers need to accept the limits of probabilistic methods in conditions of ambiguity and deep uncertainty that characterize climate change. Encouraging overconfidence in the realism of current climate model simulations or intentionally portraying recognized ignorance incorrectly as if it was statistical uncertainty (Knightian risk) can lead to questionable policy outcomes.

This analysis raises questions as to whether the path we are currently on for developing and evaluating climate models (NRC 2012) is the best use of resources for supporting policy making (Katzav and Parker 2015). Exploring alternative model structures is a rich and important direction for climate research, both for understanding the climate system and for supporting policy making. Some alternative model structures include stochastic models (Mayda et al. 1999) and parameterizations (Berner et al. 2017), a multi-component, multi-phase atmosphere (Bannon 2002), network-based models (Steinhauser et al. 2011), and artificial intelligence fortified models (Voosen et al. 2018). This analysis also describes new challenges for climate scientists to develop a broader range of future scenarios, including worst-case scenarios and regional scenarios. Weaver et al. (2013) argue for expanding the ways that climate models are used for policy making. They should be considered not simply as prediction machines, but as scenario generators, sources of insight into complex system behavior, and aids to critical thinking within robust decision frameworks. Such a shift would have implications for how users perceive and use information from climate models and the types of simulations that will have the most value for informing decision making.

Acknowledgments
I would like to thank the following individuals who provided valuable comments and input for this article: Joel Katzav, Jan Kwakkel, Nic Lewis, Tim Palmer, Leonard Smith, Peter Webster, and Tomas Milanovic.

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The subtle processes in statistical downscaling and the potential uncertainty

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Climate projections are an integral part of defining the effects of anthropogenic climate change. This includes describing possible changes in the climate and helping describe possible impacts. The projections are also created with a complex chain of climate modeling and downscaling with several sources of uncertainty. These sources of uncertainty are important to consider in decision making and impact assessments to reduce the risk of a maladaptive decision. There are four main sources of uncertainty with respect to the climate projections: (1) the scenario uncertainty, reflecting the choices of society with respect to the economy, development, and emissions; (2) the global climate models' (GCMs) uncertainty; (3) the natural variability of our climate from oscillations, such as the El Niño-Southern Oscillation (Hawkins and Sutton 2009; Hawkins and Sutton 2011; Gettleman and Rood 2016); and (4) the downscaling techniques, which translate global change to local scales (Wootten et al. 2017).

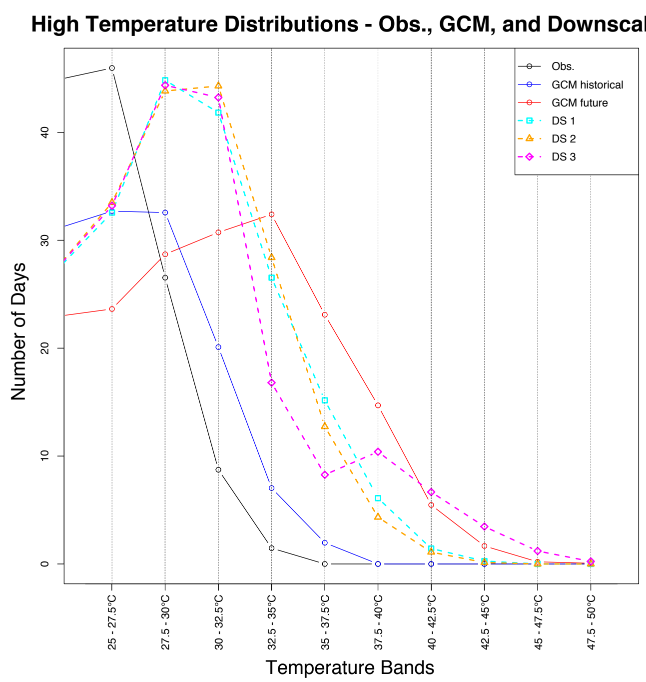
Downscaling of GCMs is performed with numerous techniques, which can be broken into two categories: dynamical and statistical (Benestad et al. 2008; Wootten et al. 2014). Dynamical downscaling uses regional climate models, which run on a finer resolution with GCMs providing the boundary conditions. Statistical downscaling relies on building a statistical relationship between GCMs and observations and using that relationship with future GCM projections to define future "observations" at local scales. Some aspects of statistical downscaling have received little attention in the literature despite the potential impacts to projections of variables important to decision making and impact assessments. In this article, I will discuss some of these aspects of statistical downscaling, their potential impacts, and recommendations for future research efforts.

Statistical downscaling processes and effects

As already described, downscaling comes in two main types: statistical and dynamical. In the case of dynamical downscaling, regional climate models (RCMs) are used to translate GCM information to local scales. Given their similar construction, it is a reasonable assumption that RCMs have similar internal sources of uncertainty as GCMs (structural and parametric; Knutti et al. 2008). However, what are the sources of uncertainty internal to statistical downscaling? Statistical downscaling is defined by creating a statistical relationship between GCMs and observations, which is effectively an exercise in statistical modeling. Therefore, one could argue that statistical downscaling has model uncertainty as described by the statistics community (Chatfield 1995), including structural and parametric. However, a close examination of the literature suggests that statistical downscaling includes more sources of uncertainty than simply the model uncertainty associated with the downscaling technique (e.g. Pourmokhtarian et al. 2016; Olyer and Nicholas, 2018). Statistical downscaling also includes numerous sets of data handling and special processing approaches. These are processes that include those implemented prior to downscaling (such as data transformations, regridding, or interpolation) and processes implemented alongside a downscaling technique (such as treatments for extreme values). These special treatments and extra processes have received little attention in downscaling literature, though some are connected with projected extremes and occurrence. How much of an effect do these subtle processes have on projected variables of interest? The answer to this question is yet unknown.

To underscore the potential effects, I focus on two such processes, beginning with treatments for extremes of temperature and precipitation. I use a simple quantile mapping (Cannon et al. 2015) to provide the downscaling using realistic synthetic inputs. These synthetic inputs are based on 1979–2005 gridMET (Abatzoglou 2013) observations from Arkansas and New Mexico and GCM data from RCP 8.5 (Van Vuuren et al. 2011; Riahi et al. 2007) driven simulations of MPI-ESM-LR (Giorgetta et al. 2013) for 2070–2099 used in the CMIP5 (Taylor et al. 2012).

In statistical downscaling, situations arise where GCM projected change pushes the downscaling beyond the historical distribution of a variable. In such cases, an additional process is used to estimate the extremes, which cannot be determined by the downscaling technique alone. These are called tail adjustments, which may have an impact on projected extremes, even if the downscaling technique, GCM, and emissions scenario remain the same. Figure 1 illustrates an example of historical observations, GCM historical and future projections, and downscaling with tail adjustments. Consider our synthetic observations for a site in New Mexico, where daily high temperatures never rise above 95°F (35°C). Quantile mapping with the GCM would push the downscaled values beyond the observational range. In this situation, quantile mapping cannot build a robust relationship between the GCM and the observations. A tail adjustment is required. But which one? For this illustration, I have implemented quantile mapping with three such tail adjustments: (1) a constant value correction, which is the difference between the maximum observed and maximum historical GCM value (similar to Deque 2007, hereafter DS1); (2) a constant value correction based upon the largest ten values of the observations and historical GCM (hereafter DS2); and (3) a correction factor calculated based on a linear regression of the correction factor for the largest ten values of the historical GCM and observations prior to implementing



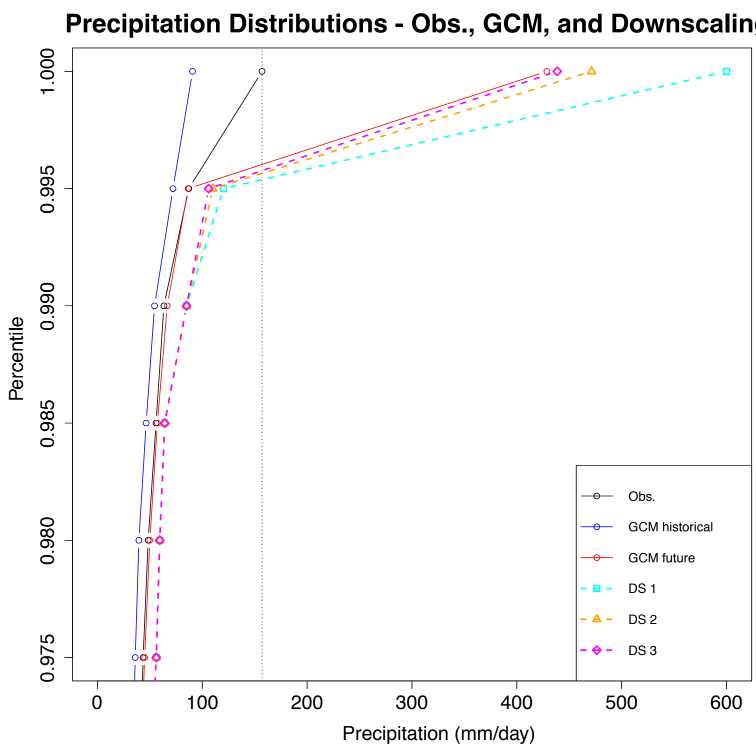
	Projected Change
GCM	**43 days**
DS1	**23 days**
DS2	**18 days**
DS3	**30 days**

Figure 1. Distribution of daily high temperatures at the high tail of the distribution as defined by the number of days per year that fall into each temperature band (°C) for the synthetic observations (Obs.), historical and future GCM, and downscaling done with each of the three tail adjustments (DS1, DS2, and DS3). The table shows the projected change in the climatology of the number of days high temperatures are greater than 95°F (35°C) for the GCM and each of the three tail adjustments. Location is approximately 108.558°W, 34.108°N – South of Agua Fria Mountain, New Mexico.

the tail adjustment divided by ten (hereafter DS3). Each correction factor is added to the GCM future value, which quantile mapping is attempting to downscale. Applying these three tail adjustments with the same downscaling technique, GCM, and observations, the downscaling is identical until the tail adjustment is activated. What does this mean for the projected change in the number of days the high temperature is greater than 95°F (35°C)? The GCM for this region suggests that the projected increase is 43 days per year (~6 weeks), but the downscaling (with three different tail adjustments) suggests an increase of 18 to 30 days per year (~2–4 weeks). This range may matter, but current literature provides little guidance as to which tail adjustments provide the highest skill and if the uncertainty is reducible.

Understanding and predicting precipitation extremes is also of interest to understand risk in a changing climate. If the same tail adjustments previously defined are used with observed and GCM precipitation from Arkansas, how are projected precipitation extremes different? Figure 2 focuses on annual 1-day maximum precipitation (rx1day; Karl et al. 1999). Applying quantile mapping with the synthetic observed and GCM precipitation, the tail adjustments again cause the downscaling to diverge at the end of the precipitation distribution. Examining the change of the rx1day climatology, the GCM suggests an increase in precipitation extremes by ~2 inches (50 mm). The downscaling (with the three tail adjustments) suggests an increase of 2–3.5 inches (50–90 mm) for the precipitation extremes. Which of these tail adjustments are appropriate? Which of these adjustments have the highest skill for precipitation extremes?

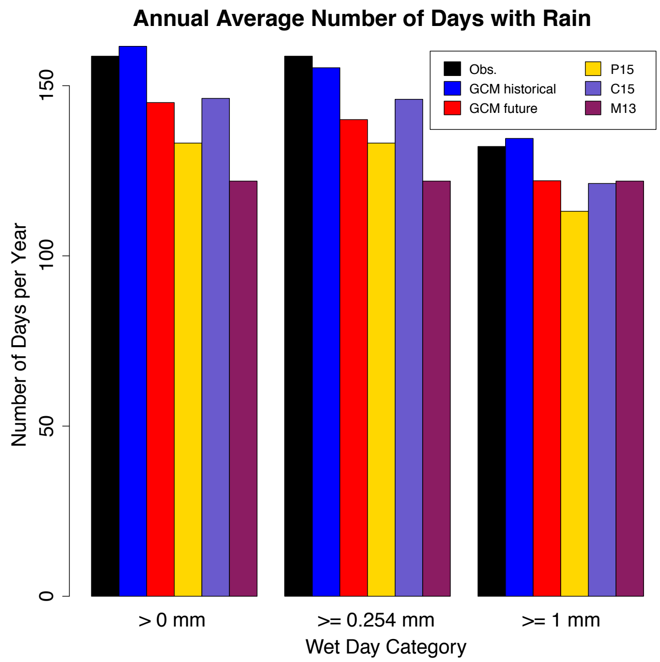
Tail adjustments are one of several aspects that can affect statistically downscaled projections. In GCMs, there is a tendency to over produce precipitation at small amounts (Pendergrass and Hartmann 2014), causing a tendency for GCMs to overestimate the wet day fraction. Some downscaling efforts attempt to correct this bias using a process referred to as a trace adjustment. Given their nature, different trace adjustments may impact the projected frequency of rain events. Consider the



	Projected Change
GCM	**46.03 mm**
DS1	**87.17 mm**
DS2	**54.67 mm**
DS3	**43.73 mm**

Figure 2. Cumulative distribution of daily precipitation at the high tail of the distribution for the synthetic observations (Obs.), historical and future synthetic GCM, and downscaling done with each of the three tail adjustments (DS1, DS2, and DS3). The table shows the projected change in the climatology of the annual 1-day maximum precipitation for the GCM and each of the three tail adjustments. Location is approximately 92.475°W, 34.858°N – Northwest of Little Rock, Arkansas.

same synthetic precipitation from Arkansas (observations and GCM) used previously but with the quantile mapping now using the following three trace adjustments. First, Pierce et al. (2015; P15 in Figure 3) define different wet day thresholds for the GCM and observations in order to correct the GCM wet day fraction. Second, Cannon et al. (2015; C15 in Figure 3) substitute values from a uniform distribution greater than zero and less than 0.05 mm/day for all values less than 0.05 mm/day in the inputs (GCM and observations) and set all values less than 0.05 mm/day in the downscaled output to zero. Third, Maraun et al. (2013; M13 in Figure 3) define a wet day as values > 1 mm/day in all inputs. While one can choose what a wet day ultimately is in the output of downscaling, we can observe that there is a difference regardless of the post-downscaling threshold for a wet day. If a wet day is a day with rainfall greater than the standard for trace precipitation (0.254 mm), then the GCM projects 15 fewer wet days per year, while the three chosen trace adjustments range from 13 to 38 fewer wet days per year.



	Projected Change
GCM	-15 days
P15	-26 days
C15	-13 days
M13	-38 days

Figure 3. Annual average number of days with rain for different wet day categories for the synthetic observations (Obs.), historical and future synthetic GCM, and downscaling done with each of the three trace adjustments (P15, C15, and M13). The table shows the projected change in the climatology of the annual number of days with precipitation (≥ 0.254 mm) for the GCM and each of the three trace adjustments. Location is approximately 92.475°W, 34.858°N – Northwest of Little Rock, Arkansas.

The point of this exercise is not to say which method is best suited for each extra process in statistical downscaling. It is out of the scope to explore the sensitivity to changes to each process and downscaling method here. Rather, the purpose of this article is to illuminate the potential source of uncertainty that these subtle extra processes could provide. At this juncture, how sensitive statistical downscaling methods are to extra processes (tail adjustments, trace adjustments) is not well known. Statistical downscaling requires building a statistical relationship between observations and a GCM. Should these processes affect either the input (observations or GCM) or the output, then the resulting projections are also affected. Therefore, these processes should be considered carefully as a potential source of uncertainty in statistical downscaling, which can be explored and reduced. In addition, statistical downscaling has been used to inform several impact related studies, with little consideration given to some of these subtle aspects of statistical downscaling (e.g., Werth and Chen 2014; Basso et al. 2015; Parmesan et al. 2015; Gergel et al. 2017). If such subtle processes affect the frequency and intensity of events, could they also influence impact assessments, which make use of the output of statistical downscaling?

Impacts and future direction

The little attention given to the subtle processes connected to statistical downscaling leads me to raise some questions regarding the associated skill and uncertainty. For each class of these extra processes (e.g., tail adjustment, trace adjustment, interpolation), which method has the highest skill? Are some downscaling techniques more sensitive to such subtle processes? Do these subtle processes introduce enough variability to affect our confidence in projections created with statistical downscaling, particularly for the extremes and occurrence of events? Is such variability translated into the results of impact modeling? Such questions in the realm of statistical downscaling may be answered by a series of sensitivity studies. What the answers mean for assessing the impacts of a changing climate is another aspect. For many planning efforts, summary information on a changing climate may be all that is needed. For more expansive efforts to assess impacts, some decision makers desire and require more localized information.

This article illustrates some of the challenges to statistical downscaling and potential sources of uncertainty. Without the answers to the science questions raised here, it is difficult to say the exact effect on planning efforts beyond what I have shown here. However, the answers to such questions can provide guidance for how much care should be taken when using or creating statistically downscaled projections for planning efforts.

All of this is not to state that statistical downscaling has no value for planning and impact assessments. Numerous studies have made use of statistical downscaling for impacts assessments and demonstrated the added value (Ivanov and Kotlarski 2017, Lanzante et al. 2018). Rather, it is important for those using statistically downscaled projections to be aware of these issues, the guidance available, and continue their planning efforts. For the downscaling community, we have incorporated these different processes as part of statistical downscaling. As we continue our work on the added value of statistical downscaling and attempt to identify, characterize, and reduce sources of uncertainty in downscaling, our evaluations should not be limited to the downscaling technique alone but include these extra processes. This is not merely for the advancement of our understanding and modeling of the climate but to ensure the resulting output can be used properly with respect to the strengths and limitations of using climate projections in adaptation planning.

Acknowledgments
My thanks to my colleagues in the network of the Climate Adaptation Science Centers for providing a review of this article. Readers who are interested in the synthetic data and calculations done for this article are welcomed and encouraged to contact me (amwootte@ou.edu).

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Addressing uncertainty in adaptation planning for agriculture

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Scientists project that temperatures will increase about 1°C by 2050 (IPCC 2007, 2013). Agriculture has been influenced by recent alterations in climate, and the impacts will increase with climate change (IPCC 2014a; McCarl et al. 2016; Fan et al. 2017). Thus, agricultural adaption to climate change in the next 25 years is inevitable (Rose and McCarl 2008; McCarl 2015). There are many uncertainties, however, associated with adaptation in regards to the extent of climate change, agricultural impacts, resource availabilities, land usages, and market responses. We are also uncertain about the pace of technological progress, adaptation practice effectiveness, and stakeholder adoption (IPCC 2014a; Fan et al. 2017). While uncertainty in climate mitigation has been discussed (Yohe et al. 2004; Kim and McCarl 2009; IPCC 2014b), there are few papers addressing uncertainty in adaption. Here, we will discuss adaptation uncertainty.

Uncertainties in adaptation planning

Uncertainties in agricultural adaption planning are not only about climate but are also associated with agricultural effects, technological progress, stakeholder actions, and the interactions among them. The uncertainty in climate predictions (see Curry article) adds to the uncertainty involved with agricultural adaptation planning through alterations in temperature, precipitation, soil moisture, heat stress, and growing seasons (Adams et al. 1990, 1995; McCarl et al. 2016; Fan et al. 2017). Also the threat from increasing severity of extreme events has implications for agricultural productivity (IPCC 2013), but associated extreme events forecasts are not commonly available.

Uncertainty in agricultural adaptation needs

Adaptation planners must manage uncertainty that arises in our ability to estimate agricultural consequences of changes in climate and its extremes but are not always certain of what is subject to change. In many cases the projected amount of climate change exceeds past observations, so extrapolation is questionable. Our ability to simulate the impacts outside of the realm of historical observations is also limited. In the following, we discuss major uncertainty factors for adaptation.

a) Technological progress: Agriculture technological progress is hard to predict but drives agriculture and can be a means of adaptation (Chang et al. 2011). For example, the average 2014–16 US corn yields were more than 4.6 times those in 1949–51, while output per unit input was about 2.5 times greater. However, technological progress is slowing down (Andersen et al. 2018), and Villavicencio et al. (2013) identifies climate as one cause. Current climate simulation models, such as those used in assessments (see Reilly et al. 2003), do not include technical progress. Furthermore, statistical extrapolation of technical progress may be imperfect as it is difficult to cover all the dimensions of climate change (i.e., extremes are difficult), plus the extent of climate change may exceed the range of historical observations.

Also technical progress depends on research investment, which in some cases has been declining causing lower increases in productivity (Pardey et al. 2013). Additionally it is difficult to forecast innovation (Armstrong et al. 2015). Thus, we are uncertain whether the possible negative effects of climate change will be fully or partially offset by technologically induced growth in productivity.

b) Demand growth: Demand for agricultural goods increases with population and income. Global population projections are for 1.9 to 5.7 billion more people in 2100, which requires about 25% – 75% more food. Moreover, income is projected to grow, increasing meat demand within the middle class and, in turn, livestock feed demand (Robinson and Pozzi 2011), further applying pressure on agriculture. Demand can also be altered by consumer preferences and policy changes, such as relaxation of the one child policy in China or the US ethanol policy that substantially altered US corn demand (Jones et al. 2017).

c) Broad nature of climate effects: Climate change influences agriculture through alterations in temperature, precipitation, water supplies, evapotranspiration, soil moisture, pest incidence, extreme weather events, and fire incidence among many other factors (McCarl et al. 2016; Fan et al. 2017). Anticipated changes in crop, milk, and meat yields; pest damage losses; livestock mortality; and livestock fecundity are all relevant to adaptation planning. Furthermore, the impacts vary substantially by region, crop, grassland incidence, and livestock populations. Maize in southern Africa, wheat in South Asia, and rice in Southeast Asia are staple foods where yields are projected to decrease, which could worsen food security (Lobell et al. 2008), raising a major adaptation challenge.

d) Practice efficiency: Climate change affects agricultural practice efficiency and can increase costs. For example, farmers may have to apply more pesticides (Chen and McCarl 2001; Wolfe et al. 2008). Also greater water demands may increase surface and ground water needs and associated energy costs (Reilly et al. 2003; Chen et al. 2001a).

e) Water: Climate change increases the water-related uncertainty directly and indirectly. An increase in the evapotranspiration rate coupled with a decrease in soil moisture and an increase in irrigation demand (Adams et al. 1999). However, regionally less rainfall coupled with climate induced increases in nonagricultural demands can decrease freshwater availability (Chen et al. 2001a; Rodell et al. 2018).

f) Extreme events: Extreme events can damage the agriculture sector. For example, heat waves in 1995 and 1999 killed nearly 5,000 US cattle (Hahn et al. 2001). Hurricanes (Chen and McCarl 2009), hail storms, flooding, and heavy rainfall can also greatly diminish production as can increases in the frequency of El Niño events (Chen et al. 2001b).

f) International trade: Climate change varies across regions, which influences agricultural production and comparative advantage, altering trade flows (Baldos and Hertel 2015). Trade alterations are a possible adaptation, where countries facing yield reductions can import commodities to protect domestic food security (Butt et al. 2006; Lobell et al. 2008), but the extent of this is uncertain.

g) Adjustments in infrastructure: Uncertainty arises with respect to agricultural infrastructure and needed investment. Existing flood risk infrastructures may have to adjust operations to adapt to changes in rainfall frequency, extreme events, and sea level rise (Gersonius et al. 2013; Cinner et al. 2018).

h) Challenges in simulation: One way to project effects and gains from adaptation involves the use of crop, livestock, or hydrology simulation models. However, it is difficult in these models to fully reflect the multidimensional nature of climate change and the uncertainty therein. For example, most crop models ignore pest interactions, assume water is fully available, and omit effects of hurricanes, hailstorms, and other damaging weather events. Furthermore, combinations and permutations of scenarios may need to be run to represent the full scope of climate change — possibly yielding results that are difficult to synthesize and interpret (Asseng et al. 2013).

Uncertainty from time

Agriculture adaptation can include long-term investments, such as building dams, irrigation systems, and funding of agricultural research and development (Fan et al. 2017; McCarl et al. 2016). These are often costly and take substantial lead-time to implement. Climate change may also influence the functioning and performance of infrastructure, so the flexibility and ability of infrastructure to evolve is very important to adaption planning (Hallegatte 2009; Gersonius et al. 2013).

Uncertainty in stakeholder reactions

Adaptation implementation may or may not require public involvement, as they constitute public goods. Many adaptations are implemented by individuals acting in their own best interests, for example shifting crop mixes, changing irrigation schedules, and altering planting dates. However, some adaptations require public action, such as irrigation facility construction and crop variety development. Cases also exist where producers are severely constrained in terms of information, resources, and human capital availability. Thus, adaptation projects contain uncertainty about the amount of needed public investment, extent of stakeholder participation, incentive design, and time to achieve implementation (Fan et al. 2017). Furthermore, stakeholders may vary in recognition of the need to adapt (Hallegatte 2009).

Considering uncertainty in adaptation planning

The above uncertainties coupled with the complexities of social-ecological systems raise analytical challenges for adaptation planning (IPCC 2014a). The following should be considered in adaptation appraisals to reflect uncertainty.

Meeting different information requirements for adaption planning

The IPCC (2014a) emphasizes the need for a variety of tools to address the scope, complexity, and uncertainty of adaptation planning. Involvement of multiple stakeholders is important, and analysts must realize that stakeholders have different preferences, orientations, and understandings of climate change. Use of multiple tools, such as brochures, TV, and two-way radios, can improve communication.

Evaluating adaptation possibilities

Implementation of many adaptation strategies requires public intervention. To supply money, adaptation funds have arisen, including the Green Climate Fund established by the UN Framework Convention on Climate Change. Applications for such funds are required and need evaluation. Evaluation criteria have been proposed (McCarl et al. 2016; Fan et al. 2017), including:

- *Additionality:* The adaptation action that would be adopted in the absence of adaptation funding. A number of possible adaptations may already be in use or may be done autonomously by decision makers and funding may not be necessary.
- *Permanence:* one major question is how long will an adaptation be effective. For example in a sea level case, permanence may involve appraisal of the range of sea levels for which the adaptation works.
- *Maladaptation:* to what extent will the adaptation benefit one group but worsen the situation for other groups.
- *Uncertainty:* how confident is one of the extent to which this adaptation reduces vulnerability. Here estimates are needed of the probability given certain degrees of climate change that damages will be reduced.
- *Transactions costs:* to what extent will funding be transmitted through to the implementing parties, like farmers and water managers.

Reducing risks by selecting "no-regret" strategies

One means of reducing risk is choice of low-cost and low-risk possibilities that return benefits under a wide variety of climate outcomes (Hallegatte 2009). Purchasing crop insurance, building irrigation infrastructures, and developing drought resistant crops are "no-regret" examples. However, strategy effectiveness is expected to diminish as climate change increases (Parry et al. 2009).

Monitoring and adjusting adaption planning during implements

Monitoring plays an important role in tracking adaption success and evolving strategies (IPCC 2014a). It helps to reduce cumulative uncertainties and to adapt the plan so it is more suitable. Monitoring also provides updated information on adaptation effectiveness and allows for improvement over time.

Using reversible and flexible options at initial stage

Adherence to rigid adaptation policies can contribute to risk. Some adaption plans (e.g., flood preventing infrastructure) are costly and, while typically defined for a concept like a hundred-year flood, are not necessarily going to be effective in the face of changing probability distributions of yields and hydrology (Milly et al. 2008; McCarl et al. 2008). When faced with such developments, it is important to use reversible and flexible strategies to allow alterations in the face of an evolving climate (Hallegatte 2009; Gersonius et al. 2013).

Reduce asset fixity time horizon

Shorter term, more flexible alternatives may be preferred to long-term infrastructure investment as a means of reducing uncertainty exposure (Hallegatte 2009). For example, one might plant annual crops rather than long-lived trees and also use less expensive, faster irrigation water supply possibilities rather than long-term hard infrastructure.

Placing a lower confidence interval on potential planning In a mitigation context, Kim and McCarl (2009) propose to lower the expected results from carbon projects by a discount related to project performance uncertainty. A similar procedure could be applied to discount adaptation practice performance uncertainty as an input to project comparison.

Conclusion

Agricultural adaptation is inevitable in the next 25 years. But implementation is plagued by uncertainty. We are not confident of the full extent and amount of future climate change or of the resultant vulnerability of agriculture. Such a situation raises tremendous adaptation planning challenges. The possible strategies to reduce the uncertainty in agriculture adaption planning include but are not limited to increasing the variety of tools, carefully designing incentive programs, evaluating key aspects of potential applications, selecting "no-regret" strategies, monitoring, using reversible and flexible strategies, favoring short-term relative to long-term fixed alternatives, and discounting uncertainty.

Acknowledgments

This material is based upon work partially supported by the National Science Foundation under grants addressing Innovations at the Nexus of Food, Energy, and Water Systems numbered 1639327 and Decision Support for Water Stressed FEW Nexus Decisions numbered 1739977.

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Uncertainty and fisheries management

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One of the many ways that humans benefit from marine biodiversity and ecosystems is through fisheries. Globally, marine fisheries landings amounts to approximately 80 million tonnes annually in the 2000s (FAO 2018). If unreported catches are taken into account, fisheries catches may reach up to 130 million tonnes per year (Pauly and Zeller 2016). Annual gross revenues from reported landings was estimated to be around $100 billion USD annually, directly or indirectly supporting the livelihood of about 10–12% of the world's populations. Sustaining the contributions of this living marine resource requires careful management.

Climate change is affecting fish stocks worldwide as abundance and productivity of fish stocks (including invertebrates and fishes) are sensitive to changes in ocean variables such as warming, deoxygenation, acidification, and alteration of primary production under increasing greenhouse gas concentrations (Pörtner et al. 2014). In general, fish stocks are shifting their distribution poleward and into deeper waters, with increasing dominance of warmer water species, changing body size and phenology, and redistribution of fisheries productivity (Cheung 2018). Climate change, therefore, elevates the risk of long-term viability of marine species, functioning of marine ecosystems, and sustainability of fisheries. A global assessment of the risk of climate impacts on 825 marine fishes and invertebrates suggests that 60% (499 species) of these species are projected to be at very high risk (i.e., these species are predicted to have a one in five chance of extinction) under high greenhouse gas emission scenarios (Representative Concentration Pathway 8.5) and "business-as-usual" fishing levels (Jones and Cheung 2017; Cheung et al. 2018).

Changing ocean conditions have now become an important challenge for effective management of fisheries resources (Perry et al. 2010). Fisheries management that fails to account for climate change effects on fish stocks may underperform in achieving their objectives and can even lead to fisheries collapse. For example, in the Gulf of Maine, ocean warming might have increased juvenile mortalities of Atlantic cod (*Gadus morhua*). Catch quotas that were set by management agencies and followed by fishers without consideration of such climate effects are suggested to be a factor driving the continuous decline of the cod population (Pershing et al. 2015).

Unfortunately, we don't have a crystal ball to tell us exactly what will happen in the future to advise fisheries. Instead, we could better understand and characterize uncertainties to inform the design of fisheries management to cope with such uncertainties. This article aims to discuss various ideas about fisheries management with uncertainties associated with climate change.

Uncertainties of coupled human-natural marine systems

The relative contributions of uncertainties of future changes in coupled human-natural marine systems vary between different organizational, temporal, and spatial scales (Cheung et al. 2016a). Uncertainties about the future of the ocean and fisheries come from different sources, including internal variability, model uncertainties, and scenario uncertainties (Cheung et al. 2016b). While climatic scenario uncertainties are generally much larger in the global scale, the relative importance of internal variability is much greater in some ocean regions (e.g., high climatic internal variability in the North Pacific) and in smaller spatial scales (Rodgers et al. 2014; Frölicher et al. 2016; Figure 1). These internal variabilities, generated from inherent processes of complex systems, are intrinsic not only to climate but also ecological and socioeconomic systems. At the same time, for fish stocks and fisheries, intensive fishing contributes to their direct mortalities often at a higher level than natural mortalities, while catches are dependent on the abundance and fishing levels. Therefore, uncertainties for fish stocks and fisheries may be dominated by variations in the seafood markets, fisheries management, and pathways of societal changes (e.g., population growth, consumption pattern) that drive changes in fishing pressure and mortality rates of fish populations. Pathways of societal changes will also partly affect greenhouse gas emissions and, thus, climate change scenarios as well as regional and global ocean governance. At the same time, climate change will affect the effectiveness of fisheries management measures. These changes in human drivers on oceans and fish stocks contribute to uncertainties of future scenarios. In addition, gaps in our knowledge about the system and

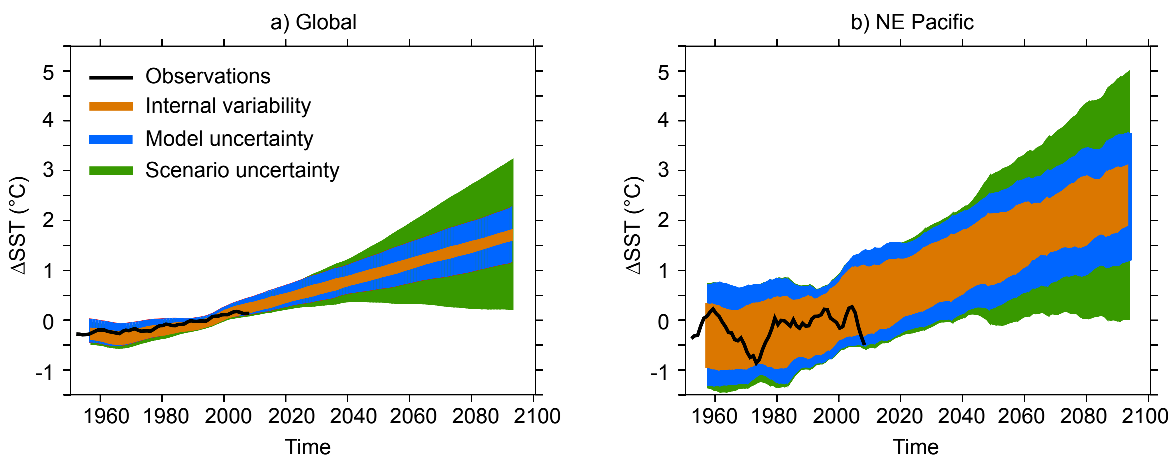

Figure 1. Time series of observations (black line) and uncertainty ranges due to internal variability (orange), model uncertainty (blue), and scenario uncertainty (green) for annual average sea surface temperature (SST, 10-year running mean) for (a) global mean and (b) Northeast Pacific relative to the 1986–2005 mean (Cheung et al. 2016).

limitation of modeling tools are also important sources of uncertainties.

Characterizing uncertainties of coupled human-natural fisheries systems could help inform the development of effective approaches to fisheries management under the changing climate. Exploration of uncertainties within coupled human-natural fisheries systems can be undertaken through the use of simulation models and scenarios. Projections can be made from ensemble members of climate-living marine resource models with different properties of internal temporal or spatial variability as well as different climate and fishing scenarios.

Different degrees of uncertainties of the coupled human-natural marine system and the levels of controllability may be more effectively managed by different strategies and approaches (Figure 2). Controllability of marine systems also covaries with uncertainties over temporal and spatial scales. Particularly, for fisheries, controllability is higher at local and national scales (e.g., within the Exclusive Economic Zones) relative to regional and global scales (e.g., in areas beyond national jurisdictions). When the system is highly controllable and uncertainties about the future are low, it may be most effective to implement optimal control tactics. Optimal control tactics generally involve "predict-then-act," such as determining catch or fishing quotas based on short-term predictions (Bowyer et al. 2015). However, in situations where controllability is low, hedging or robust decision making may become more favorable. These are interventions that seek to minimize the potential negative consequences or "regret," such as protecting critical habitats of fish stocks. In contrast, high uncertainty and lack of control of the system might favor the use of scenario planning. Specifically, scenario is used as a planning tool to evaluate the outcomes of different actions, policies, and social-economic development. If effective implementation, monitoring, and control of the fisheries are possible, active adaptive management will likely to be successful in continuously adjusting fisheries and their management based on updated knowledge generated from planned data-collection, experimentation, and analysis.

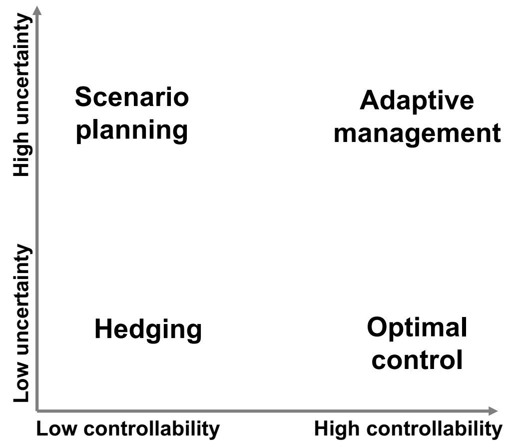

Figure 2. Approaches to fisheries management under different levels of uncertainty and controllability of the coupled human-natural marine systems (Peterson et al. 2003).

The use of scenario for fisheries management under uncertainty

Scenario planning can help integrate scientific, local, and traditional knowledge to deliver pathways of change in coupled human-natural marine systems under global change. Scenarios are representations of possible futures for one or more components of a system under its drivers of changes, including alternative policy or management options. There are generally four types of scenarios: exploratory scenarios, target-seeking scenarios, policy-screening scenarios, and retrospective policy evaluation (Figure 3). These different types of scenarios generally contribute to different decision-making contexts.

Exploratory ("story-line") or target seeking scenarios are useful for longer-term strategic planning and agenda setting exercises in which controllability is low while uncertainties are high. The exploration of projections from scenario pathways helps inform plausible trajectories that could be realized in the future in order to inform policy decisions (Jones et al. 2015; Sumaila et al. 2017). Target seeking scenarios are particularly useful

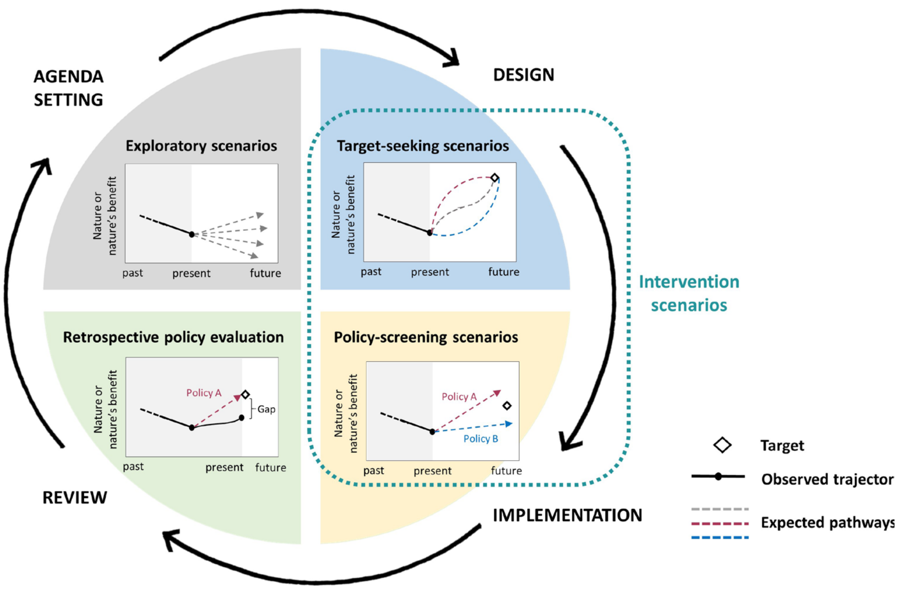

Figure 3. Four types of scenario planning approaches and their decision-making context (IPBES 2016).

when clear strategic goals and targets are available and the scenario exercise would help to identify different potential pathways to achieve them.

In contrast, policy-screening scenarios are applicable for identifying specific interventions. For example, for tactical fisheries management, management system evaluation (MSE) is one of the main approaches to assess the performance of fisheries management options under different management and climate scenarios (Link et al. 2012; Tommasi et al. 2017). MSE is particularly applicable to fisheries and their time and spatial scales that have relatively higher controllability in which management measures could be effectively implemented.

A combination of optimal control, adaptive management, and scenario planning should be an effective approach towards managing fisheries under the changing climate. Variations in the level and characteristics of uncertainties and controllability over different components of the coupled human-natural fisheries systems over different time and space horizons render the need of multiple strategies and tactics. Specifically, short-term adaptation to climate change may result in pathways to long-term sustainable development. In systems where controllability is high (e.g., strong governance, good system understanding), precise short-term interventions informed by scientific forecast and predictions could help adjust fishing practices and fisheries management to improve their performance (Buizer et al. 2016; Dunn et al. 2016; Hobday et al. 2016). For longer time frames, designing management systems with flexible and learning-based collaborations and decision-making processes that involve multiple stakeholders, often at multiple governance levels, can improve the adaptiveness of fisheries management (Schultz et al. 2015).

Progresses in scenario planning for fisheries

A wide range of models and scenarios are available for management of fisheries under climate change, but important gaps exist. Existing models and scenarios need to be better linked in order to improve understanding and explanation of coupled social-ecological systems (Cheung et al. 2016a). Particularly, the development of multi-scale scenarios that link global society changes, such as the Shared Socioeconomic Pathways currently being developed to aid assessment of climate vulnerability and response with fisheries-relevant and regional-to-local scale changes (Maury et al. 2017).

There are increasing efforts to integrate and distribute available information on marine ecosystems in a more efficient manner. Capacity to use models and scenarios, and the availability of data and knowledge to support such efforts, vary largely between regions in the world. Large-scale efforts to develop such capacity and make data and information widely available would facilitate the development of fisheries management for the uncertain future. Knowledge-based centers that bring together all the information to support decision-making for ecosystems seem to be a prerequisite for avoiding fragmented views and poor data integration.

In summary, fisheries management needs to operate under uncertainty in the changing climate, but strategies and approaches are available. The scope for effective fisheries management to achieve goals and targets of sustainable ocean development, however, is likely to be limited with unabated climate change. This highlights the importance of undertaking both climate mitigation as well as implementing interventions in fisheries management to reduce climate risks.

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Assessing and communicating uncertainty in decadal climate predictions: Connecting predictive capacity to stakeholder needs

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Decadal prediction is a relatively new area within climate science that uses initialized modeling to generate climate forecasts that extend out approximately 5 to 30 years. Interest in decadal climate prediction is motivated in part by recent advances in understanding decadal climate variability and associated predictive potential on decadal timescales (Meehl et al. 2009, 2014; Murphy et al. 2010; Goddard et al. 2012; Smith et al. 2013; Boer et al. 2016; Cassou et al. 2018). It is also motivated by the potential uses of such predictive information in climate risk management in sectors such as water resources, forestry, agriculture, ecosystems, and energy (Vera et al. 2010; Taylor et al. 2015; Bruno Soares et al. 2018; Towler et al. 2018).

From both climate science and stakeholder perspectives, decadal predictions may provide a bridge between seasonal predictions and longer-term climate projections (Goddard et al. 2012; Towler et al. 2018). By extending seasonal predictions, decadal predictions offer the potential to support climate-related decisions on interannual-to-decadal time horizons. Compared to uninitialized multidecadal-to-century climate projections, decadal predictions offer the potential to narrow the uncertainty range (due to, e.g., predictable components of decadal variability and less sensitivity to emissions scenarios; Hawkins and Sutton 2009) and better connect to the timescales of many climate-related decisions.

In this article, we discuss a project called UDECIDE (Understanding Decision-Climate Interactions on Decadal Scales) that integrates statistical and dynamical modeling research on decadal climate predictive capacity with stakeholder-oriented research on potential uses of climate-related information on decadal timescales. Like all weather and climate predictions and projections, the information in decadal climate predictions is unavoidably uncertain. Thus, understanding, assessing, and communicating predictive uncertainties are inherent components of work in this area.

The research discussed here builds on previous work on developing usable climate and weather information (Cash et al. 2003, 2006; Jacobs et al. 2005; Morss et al. 2005, 2008a; McNie 2007; Pielke 2007; Dilling and Lemos 2011; Larson et al. 2015). Key lessons from this previous work include the importance of beginning early in an effort to integrate scientific research with understanding of stakeholders' information needs, decision contexts, and constraints. This integration typically occurs through iteration between knowledge producers and users, often mediated through "information brokers" or "boundary organizations" (Cash et al. 2006; Dilling and Lemos 2011, Kirchhoff et al. 2015). Through such interactions, scientists and stakeholders can co-produce information that represents current scientific capabilities and uncertainties while also projecting onto stakeholders' decision spaces.

Starting co-production of knowledge early in the development of a new scientific area can enhance both the science and its societal benefits. With this in mind, UDECIDE was developed to investigate the intersections between decadal predictive capacity and stakeholders' information needs, and then to develop prototype presentations of decadal predictive information for testing in those decision spaces. The project is ongoing, so this article focuses on our research approach and findings to date. Our aims in discussing this research here include, first, motivating additional integrative work in decadal prediction and, second, providing an initial template for future related work on decadal prediction and communication of predictive uncertainties.

Research approach

To design and implement the UDECIDE project, our research team developed the framework in Figure 1. One research thread (right-hand side of Figure 1) focuses on understanding current and potential needs for decadal climate predictions for stakeholders in two application sectors: water resources and flood risk management. This research is identifying decision spaces that may be ready for near-term uptake of decadal climate information, given predictive uncertainties. A second, simultaneous research thread (left-hand side of Figure 1) focuses on assessing and building capacities for generating the needed decadal predictive information. As these two research threads progress, we are iterating across them to identify key entry points for communication of decadal climate prediction for decision making in the context of uncertainties, constraints, and other factors.

Weather and climate information is generally most useful to stakeholders when it is provided in terms of decision-relevant variables. As depicted in Figure 1, one research theme is exploring the potential for providing skillful decadal predictive information in terms of climate-related impact variables of interest for decisions. Examples include predicted reservoir inflow from a watershed or the probability of crossing a decision-relevant threshold such as number of days below a minimum streamflow level (Goddard et al. 2010; Towler et al. 2013; Raucher et al. 2015). Since climate-related impacts of interest often manifest at the regional or local levels, a second theme is linking decadal climate prediction to decision making at regional and local scales. To allow exploration of the intersection space in Figure 1 in depth, UDECIDE is focusing primarily on climate prediction for water resource and flood risk management in two regions of the US with different climatic characteristics and decision contexts: north-central Colorado and California.

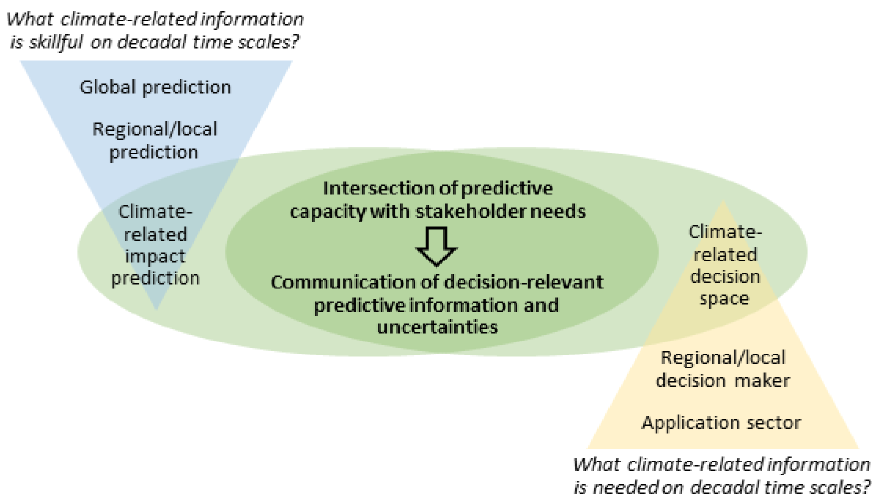

Figure 1. Framework for co-production of usable climate-related information on decadal timescales. The framework was adapted from Dessai and Hulme (2004) and the literature on usable climate and weather science and co-production of knowledge described in the text.

Given the interdisciplinary nature of this type of effort, the project team includes researchers with expertise in atmospheric science, statistics, economics, anthropology, risk communication, and water resource engineering. It also includes staff from Jacobs Engineering Group (hereafter Jacobs, formerly CH2M HILL), a private firm with substantial experience bridging climate science and practice. Partnering with Jacobs is helping our research team to identify climate-related decision spaces and impact variables for deeper investigation. It also allows us to better understand the private firm's role as a boundary organization and to explore strategies for translating decadal climate research into decision-relevant information communicated through the private as well as the public sector.

Research methodologies and emerging results

The stakeholder-oriented research began with conversations with personnel from Jacobs (functioning here as both a research partner and boundary organization) and with stakeholders employed by state, regional, and local governmental agencies involved in the two application sectors in Colorado and California. Members of the UDECIDE team then conducted a set of in-depth semi-structured interviews with flood management personnel in Colorado; these data are being qualitatively analyzed to identify key themes. We also continued interacting with Jacobs personnel and other stakeholders, and we are currently designing additional data collection in California.

The prediction-oriented research builds on previous and concurrent research on decadal predictive skill and uncertainties. Decadal prediction is an active area of research, but work to date suggests that decadal predictions currently have greatest skill for upper ocean heat content and surface temperature, with lower skill for precipitation due in part to its lower signal-to-noise ratio associated with greater internal variability (Meehl et al. 2009, 2014; Murphy et al. 2010; Goddard et al. 2013; Shaffrey et al. 2017; Yeager et al. 2018). To extend this previous work to assess predictive capacity relevant to the stakeholders' decision spaces, we are using a combination of statistical and dynamical modeling. One UDECIDE effort is employing geostatistical spatial modeling to investigate linkages between precipitation in different US regions and remote ocean temperatures (Hewitt et al. 2018). This research finds that winter precipitation in both Colorado and California is teleconnected to the spatial temperature pattern in the Pacific Ocean, suggesting that there is potential for skillful decadal predictions of winter precipitation in both regions, though more so in California.

Another UDECIDE effort is using simulations with the global atmospheric Model for Prediction Across Scales (MPAS; Skamarock et al. 2012) to investigate the dynamical linkages between Pacific Ocean temperature patterns and regional US precipitation. This research indicates the potential for decadal prediction of atmospheric rivers affecting California and other areas of the US West Coast (Figure 2; Done and Ge 2018). In particular, the model's atmospheric response to a positive Interdecadal Pacific Oscillation (IPO) ocean temperature pattern results in a southward shift in precipitation from the northwest US towards coastal California. This modeling work suggests that the effects of the IPO on precipitation over Colorado, however, are not significant.

As discussed in the next section, we are analyzing these emerging results to identify areas where potential skill intersect with needs for predictive information (darker green oval in Figure 1). Even at these intersections, however, communicating predictive uncertainty in ways that are understandable to, usable by, and useful to stakeholders remains challenging (National Research Council 2006; Morss et al. 2008b; Budescu et al. 2009; Pidgeon and Fischhoff 2011; Spiegelhalter et al. 2011; Taylor et al. 2015). Thus, UDECIDE team members are also investigating systematic approaches for processing and translating decadal predictions and associated uncertainties for use by stakeholders, including approaches adapted from seasonal climate forecasts and centennial climate projections (Towler et al. 2018).

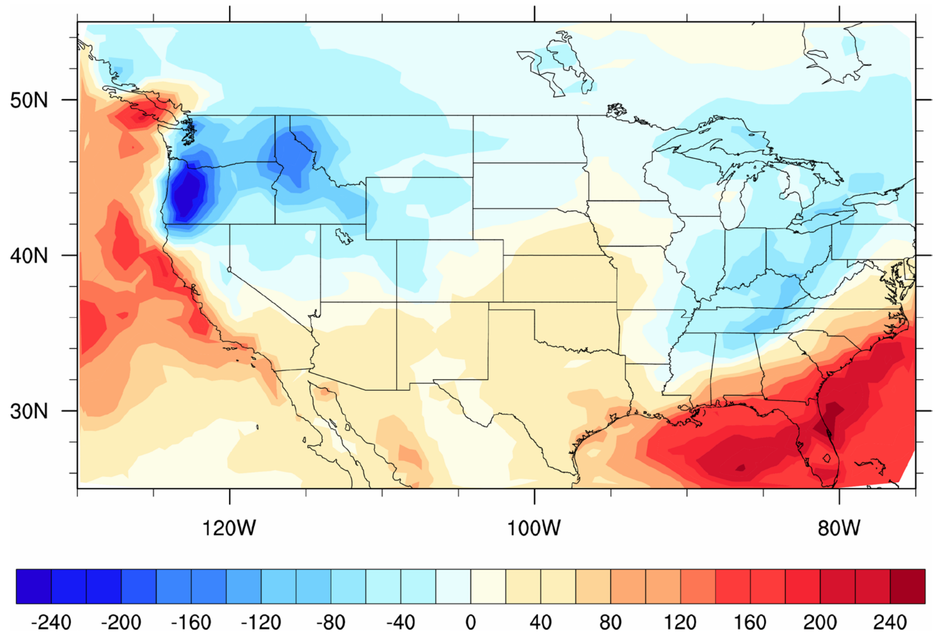

Figure 2. Difference in simulated mean winter (December-February) precipitation (mm) between the positive and negative phase of the Interdecadal Pacific Oscillation (IPO), depicted for the western US and nearby areas. Mean winter precipitation was derived from 10-member ensembles of MPAS simulations driven by ocean temperature patterns associated with each phase of the IPO.

We are currently extending this work to explore the use of hydrological and other impact models to translate the information in decadal climate predictions (and associated uncertainties) into impact predictions that are more directly relevant for stakeholders' decisions.

Identifying intersections between decadal predictive skill and decisions: Colorado and California case studies

For the flood management stakeholders in Colorado, the primary decadal climate-related decision spaces identified were infrastructure maintenance and master planning for flood control. Stakeholders discussed potential uses of climate information on decadal timescales, such as designing culverts and planning for the use of vegetation in flood control. However, they noted that their flood risk management projects incorporate freeboard — a factor above flood level that provides an extra margin of safety — and that currently the freeboard levels are greater than the signal from climate predictions and projections (given climate variability and predictive uncertainties). They also noted that the climate signal on potential future changes in flood risk is currently dominated by hydrological uncertainties, the signal from population growth and associated land use change, and other non-climate factors.

The primary climate variable of interest for this decision space is local summertime precipitation extremes, which are highly spatially and temporally variable and thus typically have significant predictive uncertainties. Recent research indicates that decadal predictions currently have poor skill for precipitation in the Colorado region of the US (Salvi et al. 2017a). Together with the other issues discussed above, this suggests decadal predictive capacity for use in flood risk management in north-central Colorado is currently limited. Decadal predictions of temperature may have skill in this region (Salvi et al. 2017b; Towler et al. 2018), and Colorado stakeholders noted that temperature changes might affect snow melt-related flooding as well as water resource and drought management decisions.

For the stakeholders in California, the decadal climate-related decision spaces identified include water reservoir operations, management of water supply quality and quantity, flood risk management, and meeting environmental regulations. Major climate-related concerns include multi-year drought, within different basins and simultaneously across basins, and several-day periods of heavy rainfall associated with atmospheric rivers. A related concern is the potential for intense precipitation events over post-wildfire watersheds, which can negatively impact water quality.

The primary climate variable of interest in these California decision spaces is precipitation in winter. Compared to summer precipitation in Colorado, winter precipitation in California has a larger signal-to-noise ratio, associated in part with connections between California winter climate and Pacific Ocean temperature patterns across a range of timescales. On subseasonal and seasonal timescales, precipitation in different regions of California is related to features such as atmospheric rivers and El Niño-Southern Oscillation (Dettinger et al. 2011). California precipitation also exhibits variability on decadal and multidecadal scales, which has been linked to decadal modes of variability with signatures in Pacific Ocean temperature patterns (Dai 2013). These connections are a likely reason for recent research results that suggest some potential decadal predictive skill in this region (Salvi et al. 2017a,b; Yeager et al. 2018; Figure 2).

This analysis suggests that there is currently more potential in California than in Colorado for developing decadal predictive information that is usable to the stakeholders involved in the UDECIDE project. Stated another way, in Colorado the climate signal is small and predictive uncertainties are large compared to the influence of other factors and uncertainties on the decisions of the flood risk management stakeholders that we interviewed. Therefore, we decided at this stage to focus on the California stakeholders for additional work on decision-relevant communication of decadal predictions and associated uncertainties.

Moving forward

Building on our research to date, the UDECIDE team is now focusing on work in the intersecting green oval in Figure 1, where potential decadal predictive skill intersects with California water resource and flood management stakeholders' decision spaces, given uncertainties. This includes investigating, in greater depth, key climate-related impact variables and the translation of decadal climate predictions into those variables on spatial and temporal scales relevant to stakeholders' information needs. We then plan to design prototype presentations of decadal predictive information in terms of these impact variables, test those presentations with stakeholders, and iterate to develop understanding of the key characteristics of usable information and effective communication of uncertainty.

Because, as noted above, uncertainty is inherent in decadal predictions, communication of uncertainty is a key component of this work. Our focus, however, is not on assessing and communicating predictive uncertainties in terms of climate variables alone. Instead, we are leveraging the experience of Jacobs and stakeholders to develop mechanisms for creating and communicating decadal predictive information and associated uncertainties in decision-relevant terms. One important step in this process is evaluating whether the potential climate signal is dominated by other sources of uncertainty in the decisions of interest, as currently appears to be the case in our Colorado study, or whether it is sufficiently strong to potentially provide usable information, as in California (Raucher et al. 2015).

This article presents a framework for improving the communication of climate-related predictive uncertainties by developing and conveying predictive information in ways that project more readily onto stakeholders' decision spaces. By discussing how we are using this framework to conduct research on the intersections between predictive skill and information needs, we aim to help the field of decadal climate prediction evolve in ways that are relevant to and valued by society.

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US CLIVAR acknowledges support from these US agencies:

This material was developed with federal support of NASA and NSF (AGS-1502208), NOAA (NA16OAR4310253), and DOE (DE-SC0016332). Any opinions, findings, conclusions, or recommendations expressed in this material are those of the authors and do not necessarily reflect the views of the sponsoring agencies.