



Choosing and Using Climate-Change Scenarios for Ecological-Impact Assessments and Conservation Decisions

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Abstract: *Increased concern over climate change is demonstrated by the many efforts to assess climate effects and develop adaptation strategies. Scientists, resource managers, and decision makers are increasingly expected to use climate information, but they struggle with its uncertainty. With the current proliferation of climate simulations and downscaling methods, scientifically credible strategies for selecting a subset for analysis and decision making are needed. Drawing on a rich literature in climate science and impact assessment and on experience working with natural resource scientists and decision makers, we devised guidelines for choosing climate-change scenarios for ecological impact assessment that recognize irreducible uncertainty in climate projections and address common misconceptions about this uncertainty. This approach involves identifying primary local climate drivers by climate sensitivity of the biological system of interest; determining appropriate sources of information for future changes in those drivers; considering how well processes controlling local climate are spatially resolved; and selecting scenarios based on considering observed emission trends, relative importance of natural climate variability, and risk tolerance and time horizon of the associated decision. The most appropriate scenarios for a particular analysis will not necessarily be the most appropriate for another due to differences in local climate drivers, biophysical linkages to climate, decision characteristics, and how well a model simulates the climate parameters and processes of interest. Given these complexities, we recommend interaction among climate scientists, natural and physical scientists, and decision makers throughout the process of choosing and using climate-change scenarios for ecological impact assessment.*

Keywords: climate change, freshwater, marine, risk assessment, threatened species

Selección y Uso de Escenarios de Cambio Climático para Estudios de Impacto Ecológico y Decisiones de Conservación

Resumen: *El incremento en la preocupación por el cambio climático se ve demostrado por la cantidad de esfuerzos para estudiar los efectos climáticos y desarrollar estrategias de adaptación. Cada vez se espera más que los científicos, los administradores de recursos y los encargados de tomar decisiones usen la información climática pero ellos tienen problemas con esta incertidumbre. Con la actual proliferación de simulaciones climáticas y métodos con reducción de escala, se requieren estrategias científicamente creíbles para la selección de un subconjunto de análisis y toma de decisiones. Al tomar de una literatura rica en ciencias climáticas y el estudio del impacto y con la experiencia de trabajar con científicos de recursos naturales y*

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encargados de la toma de decisiones, diseñamos guías para escoger escenarios de cambio climático para el estudio del impacto ecológico que reconozcan la incertidumbre irreducible en las proyecciones climáticas y se dirijan hacia malentendidos comunes sobre esta incertidumbre. Esta aproximación involucra identificar conductores locales primarios de clima mediante la sensibilidad climática del sistema biológico de interés; determinar fuentes apropiadas de información para cambios futuros en esos conductores; considerar que tan bien resueltos espacialmente están los procesos que controlan el clima local; y elegir escenarios basados en considerar las tendencias observadas de emisiones, la importancia relativa de la variabilidad natural del clima y la tolerancia de riesgo y el horizonte de tiempo de la decisión asociada. Los escenarios más apropiados para un análisis particular no serán necesariamente los más apropiados para otro debido a las diferencias en los conductores locales del clima, la relación biofísica con el clima, las características de la decisión y cómo el modelo simula los parámetros del clima y los procesos de interés. Dadas estas complejidades, recomendamos la interacción entre científicos del clima, científicos naturales y físicos y los encargados de las tomas de decisiones a lo largo del proceso de elección y usar escenarios de cambio climático para estudios de impacto ecológico.

Palabras Clave: agua dulce, cambio climático, especies amenazadas, estudios de riesgo, marino

Introduction

As in other parts of the world, in the United States natural resource management agencies are starting to prepare for the effects of climate change. Requirements to do so have been set forth in Presidential Executive Order 13514 (2010), reiterated within agencies (e.g., USDO 2009; NOAA 2010; USFS 2010), and emphasized by recent court decisions (e.g., *Pacific Coast Federation of Fishermen's Associations v. Gutierrez*). In response, scientists and managers are beginning to use climate-change projections in risk assessment and planning.

However, climate-change projections are inherently uncertain due to the future evolution of factors forcing climate change (e.g., greenhouse gas emissions), climate model error, and natural variability. To account for these uncertainties, climate projections are based on multiple forcing scenarios (either emissions scenarios [Nakicenovic et al. 2000; IPCC 2007] or representative concentration pathways [Moss et al. 2010]), multiple climate models (CMs), and multiple ensemble members (i.e., simulations with the same CM and emissions scenario but different initial conditions). The result is a dizzying array of climate-change simulations with a range of outcomes (Knutti & Sedláček 2013), where even the direction of change in key climate variables may be unclear. Downscaling global climate projections and simulating physical and biological effects typically increases this uncertainty.

Uncertainty poses substantial difficulties for scientists and managers seeking a defensible choice of climate-change scenarios in publicly visible, potentially litigious, decision-making contexts. We define *scenarios* as projections of future climate or climate-influenced environmental conditions at the scale of interest. Some managers are experimenting with alternate strategies for coping with uncertainty, such as formalized scenario-planning exercises (Weeks et al. 2011), but legal standing for their use in agency decision making is unclear. A more common approach is to limit the range of outcomes considered

by attempting to evaluate and select, a priori, the “best” of each scenario component necessary for impact assessment (e.g., global CMs, emissions scenarios, downscaling, models of intermediary effects) (Fig. 1) or to wait for advances in climate science to provide better projections.

Despite the common desire of biologists, natural resource managers, planners, and policy makers to do so, it is not possible to identify the best scenarios of change in local climate drivers or the best individual scenario components. There are, however, objective paths to choosing climate scenarios for impact assessment. We synthesized the literature that is relevant to this point and to other common misconceptions about the accuracy and utility of climate-change projections. We present both a structured approach and general guidelines for choosing and using climate-change scenarios that recognize the irreducible uncertainty of future climate and the need to develop useful climate information for decision making.

Guide for Choosing and Using Climate Scenarios

Selecting scenarios for impact assessment requires identifying the primary local- and large-scale climate drivers, determining appropriate sources of information for future scenarios of those drivers, and objectively identifying a subset of scenarios of change in these drivers for analysis (Table 1).

Step 1. Identify primary local environmental drivers

Too often, local climate-change impact assessment starts with examination of global climate scenarios. Instead, we suggest starting with biology by developing a conceptual model that links biological response to local climate and using sensitivity analysis to determine the most important pathways of climate effects.

A good conceptual model (Busch & Trexler 2003; Margoluis et al. 2009) identifies the specific biophysical linkages through which climate directly and indirectly affects a species (distribution, abundance) or organism

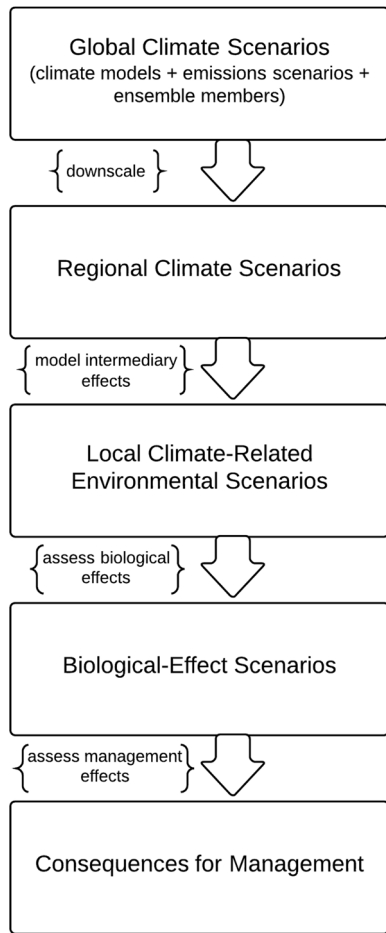


Figure 1. A common method of assessing the consequences of climate change for natural systems is a top-down impact assessment, which links, in turn, projections of global climate, regional climate, regional effects, biological effects, and responses.

(growth, survival, performance, mortality). It includes all life stages, relevant habitats, ecosystem processes maintaining and connecting those habitats, and heterogeneity in climate and ecological processes (e.g., Fig. 1 in McClure et al. 2013 [this issue]). It may include explicit linkages between climate and system response or implicit linkages determined by observed correlations.

Ecological sensitivity to climate can be characterized via empirical analysis of biological response to climatic drivers (e.g., Battin et al. 2007; Boughton & Pike 2013 [this issue]; Walters et al. 2013 [this issue]), especially at transition zones, where climate can limit performance (Baker et al. 2007; Hazen et al. 2013), and biological thresholds, where changes in local climate conditions cause nonlinear responses (e.g., stream-temperature threshold for salmon mortality [McCullough 1999]). Such analyses are sensitive to choice of biological response variable and require accounting for nonclimatic

Table 1. Process for selecting climate scenarios for ecological-impact assessments.

1. Identify primary local climate-related environmental drivers (climate drivers).
 Develop a conceptual model linking biological response to local climatic conditions.
 Determine the most important climate effect pathways and local climate drivers through sensitivity analysis, expert judgment, or other approaches.
2. Determine appropriate sources of information for future scenarios of local climate drivers that consider how well processes controlling local climate are spatially resolved (Fig. 2).
3. Objectively select (a subset of) scenarios for use in impact assessment based on whether climate-model errors significantly affect model sensitivity to global warming, effect of natural climate variability, time horizon of associated decisions, observed emission trends, and decision context and risk tolerance (Table 2).

drivers of change, spatial heterogeneity, and temporal autocorrelation (Brown et al. 2011; Hare et al. 2012). Because the magnitude of biological response depends on both system sensitivity to environmental change and the magnitude of that change, the latter must also be considered when identifying primary pathways of climate effects.

For many biological systems and species, especially marine, limitations in data and process understanding pose significant challenges (Brown et al. 2011). Where lack of information precludes quantitative sensitivity analyses, primary climate drivers can be identified using expert judgment considering the possible magnitude of projected climate changes and associated habitat responses and relative importance of affected life stages. For example, the biological review team assessing the status and extinction risk of 82 coral species found good information on projected climate-change and general effects of temperature, UV radiation, and changes in ocean pH in tropical ecosystems (e.g., Hoegh-Guldberg et al. 2011) but little to no species-specific information necessary for determining extinction risk. They, therefore, assessed climate effects with expert opinion that relied on existing knowledge of acidification and temperature effects on coral families and genera and a descriptive model of implications for coral mortality and reproduction (Brainard et al. 2013 [this issue]).

Step 2. Determine appropriate sources of climate information

The next step is to determine whether biological effects of climate change can be assessed with output taken directly from CMs or whether downscaling or modeling of intermediary effects is necessary (Fig. 2). Because each analytical step can add uncertainty, relying on output from as high up the chain toward CMs is preferred.

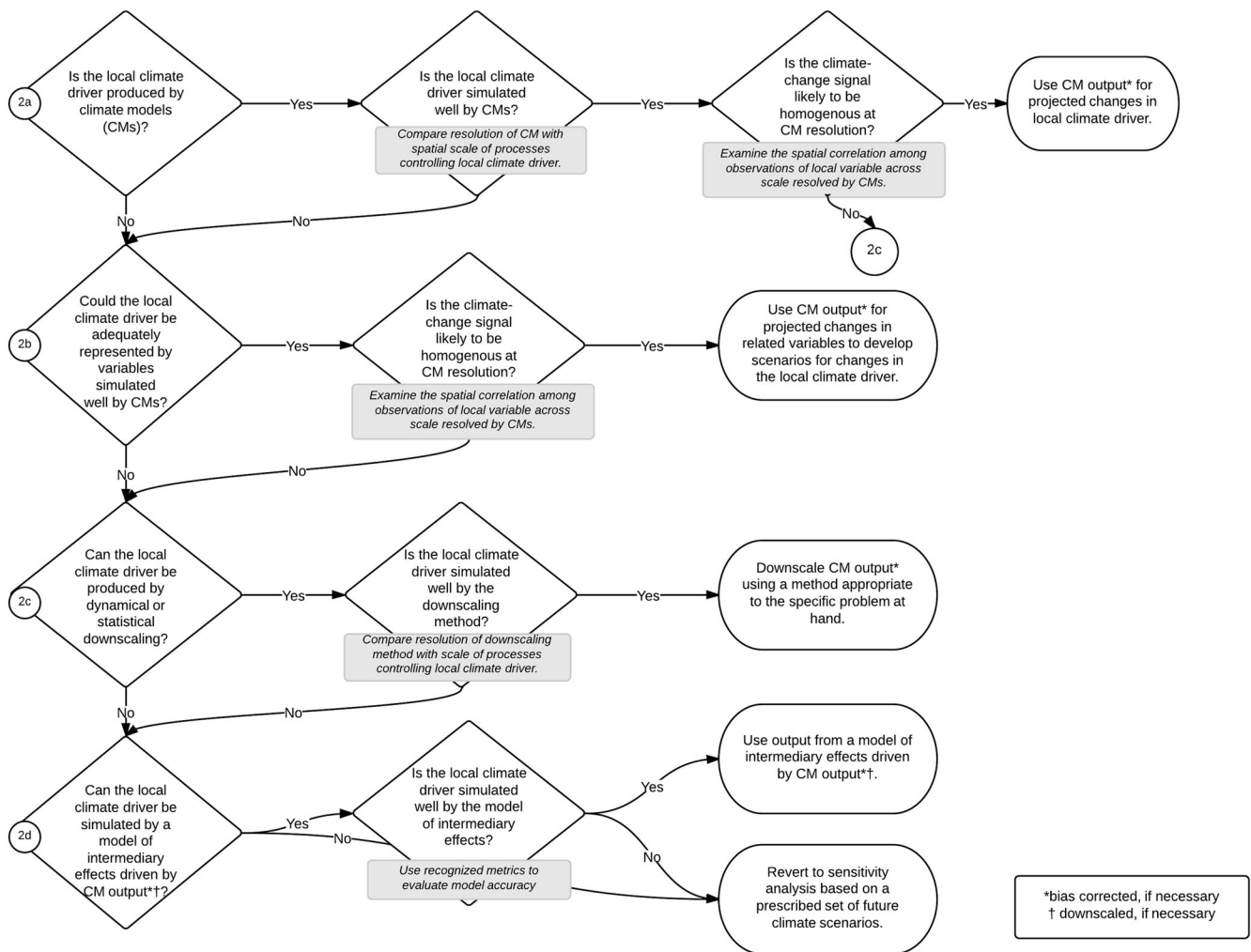


Figure 2. Steps for determining appropriate source(s) of information for constructing climate change scenarios for local climate drivers.

Step 2a: Determine whether climate model output be used directly

Current CM experiments produce output that can be used directly to develop scenarios of local environmental conditions. In addition to future air temperature and precipitation, archived CM output includes relative and absolute humidity, downward solar radiation, long-wave radiation, near-surface wind speed and direction, evaporation, sea-level pressure, land surface hydrology, upper ocean and sea surface temperature (SST), salinity, sea surface height, and sea-ice thickness, typically at monthly time-steps from transient CM runs (i.e., runs driven by time-evolving anthropogenic forcings). Output is available from the Program for Climate Model Diagnosis and Intercomparison (Meehl et al. 2007).

Long-term means (>30-year averages) from CMs should be compared with observations to determine whether bias correction is necessary (Mote et al. 2011). In the simplest bias-correction approach, the delta method,

the difference between modeled future and modeled historical conditions is applied to the observational record (e.g., monthly or seasonally). Hereinafter, we use *CM output* to refer to both bias-corrected and nonbias-corrected CM output.

Although bias correction is typically necessary, it is not always sufficient. CM spatial resolution and ability to simulate controlling processes should also be evaluated before output is applied in local impact assessments. Many ecologically important climatic processes are insufficiently resolved in recent CMs (typical horizontal resolution 100–250 km). For example, simulated coastal water temperature and salinity are typically biased in coastal upwelling zones where important physical processes operate at scales of a few to tens of kilometers (Stock et al. 2010; King et al. 2011). Applicability of CM output can be evaluated by examining the spatial correlation among observations of the variable of interest across the scale resolved by CMs. For instance, because observed air-temperature

variations tend to be well correlated over many hundreds of kilometers, biological effects related to changes in air temperature can be assessed with (bias-corrected) CM temperature projections.

Step 2b: Determine whether the local climate driver can be adequately represented by variables produced by CMs

Even if CMs do not appropriately simulate the variable of interest, CM output can be useful when the local climate driver is well correlated with variables the CM simulates well. For instance, better projections of coastal upwelling changes may be developed from well-resolved CM projections of atmospheric sea-level pressure (e.g., Wang et al. 2010) than from direct CM simulation of upwelling. Cross-scale relations were exploited to project future changes in Atlantic croaker (*Micropogonias undulatus*) juvenile survival rates. Because survival was linked to estuarine winter water temperatures controlled by surface air temperature, bias-corrected CM air-temperature projections for a region central to Atlantic croaker distribution could be used to project croaker survival (Hare et al. 2010).

Correlations between local system conditions and larger-scale climate indices, such as the North Atlantic Oscillation (NAO) or Pacific Decadal Oscillation (PDO) indices, are frequently used to elucidate historical trends and variations (Mantua et al. 1997) and sometimes to project changes over the next few decades (Van Houtan & Halley 2011). However, such relations may break down in a nonstationary climate. For example, North Pacific SST trends are expected to be driven largely by the PDO pattern for the next few decades and by anthropogenic greenhouse-gas forcing by the mid-21st century (Overland & Wang 2007).

Step 2c: Determine whether downscaling is necessary

Biological impact assessments typically require climate scenarios at a finer resolution than current CMs. Such scenarios can be created by applying a climate-change signal of coarse resolution to an observational record of finer resolution or by downscaling the climate-change signal itself to finer resolution. A common approach to the former is the delta method (Fogarty et al. 2008; Hare et al. 2010).

Downscaling may be necessary to increase the resolution of the climate-change signal in cases where CMs cannot resolve complex topography or where local climate is controlled by land and ocean interactions with the atmosphere. In statistical downscaling empirical relations between global CM output and finer-scale conditions are employed. Approaches differ with respect to data requirements, ability to capture extremes (Burger et al. 2012) on various timescales, degree to which spatial and temporal variability are derived from historical observations versus CM output, etc.

(Salathé et al. 2007; Maurer & Hidalgo 2008; Abatzoglou & Brown 2011). In dynamical downscaling, a higher resolution (approximately 10–50 km) regional climate model (RCM) is nested within a global CM. Computational demands are a limiting factor. Dynamically downscaled products are available for many atmospheric and land-surface climatic variables (e.g., North American Regional Climate Change Assessment Program [http://www.narccap.ucar.edu/data/data-tables.html]), for some CM-RCM combinations, at a resolution of 50 km for most of North America. Output from RCMs run at finer resolution is available for some regions (e.g., Salathé et al. 2010). RCM outputs must be bias corrected or statistically downscaled for many local impact-assessments (e.g., Wood et al. 2004). For all methods, validation is difficult without a high-density network of climate observations to match the downscaled grid (Lundquist & Cayan 2007), making marine applications especially challenging. Downscaled climate scenarios can provide a sense of false realism; all remain subject to errors and uncertainty in both the underlying large-scale CM projections and from downscaling.

The choice of downscaling approach is problem dependent. Close collaboration between biologists and climate scientists can be helpful in determining which methods are appropriate for a specific application. Although statistically more complicated or computer-intensive downscaling methods are sometimes associated with better performance, simple methods can provide similar or superior results (Fowler et al. 2007). When multiple factors affecting an ecological endpoint are important, a dynamical downscaling approach that ensures physical consistency among output variables may be more appropriate. When information on the relation between climate and ecological effects is limited or when ecosystem response is driven by one factor that is relatively insensitive to local effects, a simpler approach may be preferable.

Step 2d. Determine whether models of intermediary effects are necessary

A model of intermediary effects may be required to develop scenarios for scales and variables not simulated by CMs. For example, scenarios of future coastal marine habitat can be developed with coastal upwelling and estuarine circulation models using as input winds simulated by RCMs (e.g., Auad et al. 2006). In the complex topography of the western United States, where local processes control the terrestrial water cycle, statistical downscaling and hydrologic modeling were combined to assess effects of climate change on snowpack, which affects wolverine (*Gulo gulo*) denning (McKelvey et al. 2011); on stream flow and temperature, which affect trout habitat suitability (Wenger et al. 2011); and on summer potential and actual evapotranspiration, which affect wildfire occurrence and area burned (Littell & Gwozdz 2011). In

each case, downscaled climate information from a CM was necessary but not sufficient for projecting local effects of climate change. Evaluations of the ability of joint climate-biologic response modeling to replicate observed conditions can indicate the degree to which the cascade of uncertainty, caused by linking multiple models, and small errors in initial (climate) conditions lead to larger errors in projections of biologic response (Littell et al. 2011).

If needed variables cannot be derived from CM output, scenarios can be created with other information, such as observed variations or historical conditions. For example, Beer and Anderson (2011) bioenergetically modeled effects of warming on juvenile steelhead (*Oncorhynchus mykiss*) growth rates in a relatively cold and relatively warm stream. Dettinger et al. (2011) developed a worst-case winter-storm scenario for California from 19th century historical records to support emergency preparedness and planning.

Step 3. Select (a subset of) scenarios for analysis

Step 3a. Identify available scenarios

Having identified the components necessary for developing local climate change scenarios, one can identify the group of potential scenarios available for analysis. Although efforts to date have focused primarily on the range of projections from multiple CMs, emissions scenarios, and ensemble members, more recent work is also accounting for the use of multiple downscaling methods and models of intermediary effects (Maurer et al. 2010; Pierce et al. 2013).

Although perhaps it is desirable to use all existing scenarios in a multimodel impact assessment, this approach is computationally intensive (e.g., Maurer et al. [2007], where statistically downscaled projections from each emissions-CM-ensemble combination drive a hydrologic model). The IPCC's AR4 assessment report includes 21 CMs, 6 emission scenarios, and 1–5 ensemble members for each model and emissions combination (IPCC 2007). The AR5 assessment report will have over 50 CMs, many with multiple ensemble members (Taylor et al. 2012). With the proliferation of scenarios, defensible strategies for selecting a subset of scenarios for analysis remain important.

Although there are many criteria for evaluating CMs, including the ability to reproduce aspects of observed climate (Walsh et al. 2008; Mote & Salathé 2010), past agreement does not ensure reliable future prediction (Knutti 2008) and model ranking varies by metric (Knutti 2010; Overland et al. 2011), variable, temporal and spatial scale, and geographic location. There is little evidence that screening CMs through hindcast performance leads to substantially different mean projections than would result from a random sample of 6 or more different CM scenarios (Pierce et al. 2009; Knutti et al. 2010). Mote

et al. (2011) recommend that, rather than attempting to cull CMs on the basis of model robustness, analysts should use as many future scenarios as possible and avoid overweighting CMs with multiple ensemble members. However, one might consider eliminating CMs that fail to reproduce defining aspects of the system (e.g., McAfee et al. 2011) or that have errors that affect model sensitivity to greenhouse forcing. In their evaluation of climate effects on cusk (*Brosme brosme*), Hare et al. (2012) eliminated a CM that simulated ice too far south (in the Gulf of Maine) that would have exhibited unrealistic sensitivity to global warming there.

The importance of using multiple ensemble members depends on the likely influence of natural variability. For some variables, such as SST in much of the tropics, the anthropogenic trend (signal) is large relative to the natural variability (noise). In contrast, the climate-change signal in midlatitude precipitation is difficult to distinguish from natural variability until at least the 2060s (Deser et al. 2012a, 2012b). The signal-to-noise ratio can be estimated by the range of changes projected by multiple ensemble members. Where this is low, natural variability is likely to dominate changes projected by an individual ensemble member, and multiple ensemble members should be examined. For high signal-to-noise ratios, this is less important. A common practice for enhancing the signal-to-noise ratio is creating 30- to 50-year means of CM output.

Step 3b. Consider limiting scenarios based on emission-scenario characteristics

Depending on the time horizon of analysis, it may be possible to reduce the number of scenarios analyzed by including fewer emissions scenarios. For climate change over the next few decades the choice of emissions scenario is largely irrelevant. Because the projected increase in global temperature until approximately 2050 largely reflects past emissions, there is little difference across emissions scenarios before then. For later in the century, emission scenarios could be prioritized by the estimated likelihood that they represent actual future emissions. Recent (since 2006) trends in emissions are near the high end of emissions scenarios in IPCC AR4 (Peters et al. 2012). These observations, the locked-in emissions from the existing energy system, and the lack of substantial international commitment to reducing emissions, make achieving low-end scenarios (e.g., B1) increasingly unlikely (MIT 2012). Walters et al. 2013 (this issue) deem the higher of the available emissions scenarios more plausible (A1B vs. B1), whereas Brainard et al. (2013) use a range of emissions scenarios in part because they did not make assumptions about future technology or policy developments.

Step 3c. Select a scenario subset based on decision context

Table 2. Climate-change scenario selection criteria related to risk tolerance of associated management decisions.

<i>Decision characteristic</i>	<i>Implication for analysis</i>	<i>Note</i>
Risk averse (e.g., management of endangered species to avoid extinction)	Choose climate scenarios indicating the largest negative impacts or examine only climate scenarios on the basis of probable emissions scenarios.	Because worst case is drawn from ensemble of opportunity, not the real-world situation, recognize that actual effects may be more severe than projected.
Risk tolerant (e.g., plan for best case, adjust management if necessary)	Depending on actual level of risk tolerance, choose the climate scenario that indicates the best case or middle-of-the-road projections.	For effects sensitive to interannual variability, select a specific individual scenario rather than an average of multiple scenarios or choose a method for developing scenarios that preserves this variability (e.g., delta method, some downscaling methods).
Risk managing (e.g., develop strategies robust to future uncertainty by planning for a range of possible outcomes)	Select scenarios that represent the full range of existing projections, including 2 or more scenarios that indicate high- and low-end changes in local climate drivers.	The range of plausible outcomes may be larger than scenarios indicate due to the possibility of a more extreme worst-case scenario. Consider using an even number of scenarios to preclude the common tendency of users to assume the middle scenario is most probable.

The climate scenarios under consideration can be narrowed according to whether the decision making is risk averse, risk tolerant, or intended to develop robust strategies across risks (Table 2). Selecting scenarios in this way requires information about the direction and relative magnitude of biological effects across available scenarios, often qualitatively estimated based on the relative magnitude of projected change for primary climate drivers. In a risk-averse context, such as ESA listing decisions (McClure et al. 2013 [this issue]), in which the objective is to avoid worst-case outcomes, it would be important to identify and analyze the scenarios indicating the largest negative effects for the system of interest. For analyses to support a risk-tolerant approach to resource management, the best-case scenario, the central scenario, or the scenario (or delta method) average may be appropriate depending on actual levels of risk tolerance and ability to adjust management approaches in response to unanticipated conditions. (Because averaging smooths CM interannual variability when effects are sensitive to interannual variability, basing the scenario on a specific CM run or delta-method perturbation of historical time series would be more appropriate than using the multimodel average.)

In the face of an uncertain future, resource managers are increasingly encouraged to manage risk by developing conservation strategies that are robust to many conditions. Boughton and Pike (2013 [this issue]) found that restoring natural floodplain processes is a strong strategy for steelhead conservation, given multiple climate scenarios. Supporting this decision-making approach requires selecting scenarios that represent the full range of existing projections (e.g., ≥ 2 bracketing scenarios that represent high- and low-end changes in primary climate drivers [Littell et al. 2011; McKelvey et al. 2011; Wenger et al. 2011]), although the model that projects the most

change in one region or variable may show little or no changes for another. Providing an even number of scenarios helps preclude the common tendency of policy makers to choose the middle scenario under the assumption it is most likely. Providing projections for only the worst- and best-case scenarios reduces computational time and elicits a more thoughtful response.

Although the least change scenarios seem well founded, the largest change scenario in CM archives does not necessarily represent the largest plausible future change. The climate system could be more sensitive to increased greenhouse gases (Annan & Hargreaves 2006; Roe & Armour 2011), future emissions could be greater than in any of the emissions scenarios, and unforeseen climate extremes from natural variability are also possible. Decision makers should be keenly aware that managing for the largest change defined by currently available scenarios may not be sufficient to guarantee resilience.

Climate scientists carefully distinguish between climate projections, derived from scenarios of future changes in climate forcings, and climate predictions (or forecasts), which attempt to simulate the actual climate state forward in time. In contrast to previous IPCC simulations, the AR5 assessment includes climate-prediction experiments (i.e., decadal forecasts that begin with observed initial conditions). However, these predictions have limited accuracy, beyond their ability to capture the climate-change signal, because of errors in model physics and because chaotic interactions cause minor differences in initial conditions to increase over time and result in forecasts that diverge widely from nature and each other (Pohlmann et al. 2009; Solomon et al. 2011). Despite these difficulties, predictions are robust for northern Atlantic Ocean temperatures for approximately 10 years (Oldenborgh et al. 2012; Yang et al. 2013). Overall, the expected

Table 3. Common misconceptions about the utility of climate scenarios for ecological-impact assessments and decision making, implications for scenario selection and use, and links to guidelines for scenario selection.

<i>Misconception</i>	<i>Reality*</i>
<p>Pessimism about climate-change scenarios</p> <p>Climate models (CMs) do not produce output variables relevant for determining ecological responses.</p> <p>Because CMs are accurate only at continental spatial scales, CM output is unsuitable for projecting regional or local changes and effects.</p> <p>A single CM simulates all variables equally well or poorly for all locations and time steps.</p> <p>Because the projected direction of change in important variables is not the same among CMs, CM output cannot usefully inform decision making.</p> <p>The cascade of uncertainty, caused by linking multiple models, combined with the typically large range in climate-change projections means that projected biological effects are too uncertain to be useful.</p> <p>Every time a new set of climate-change scenarios is released (e.g., by the Intergovernmental Panel on Climate Change (IPCC), impact assessments must be completely redone.</p>	<p>CMs simulate a large variety of variables, including many appropriate for direct use in ecological impact assessment (step 2a).</p> <p>There are a variety of ways in which the robust output of CMs can be used to drive local biological assessments, depending on the spatial scale of controlling processes (step 2 and Fig. 2).</p> <p>Accuracy of CM simulations differs significantly by variable, temporal and spatial scale, and geographic region. This diversity must be considered when evaluating CM output for use in local impact assessment (step 2).</p> <p>Despite directional uncertainty in CM projections of some variables, robust scenarios of future conditions can be developed when biological effects are dominated by changes in other better-understood variables. In the western United States, for example, spring snowpack important for wolverine reproductive success is projected to decrease in all future scenarios as a result of projected warming, despite significant uncertainty in future precipitation (McKelvey et al. 2010) (step 1).</p> <p>Evaluations of the ability of joint climatic-biological response modeling to replicate observed conditions can be used to evaluate the degree to which small errors in initial climate conditions lead to larger errors in projections of biological response (Littell et al. 2011).</p> <p>If the assumed linkages among changes in global climate, local climate drivers, and biological effects are clearly articulated, and the ranges of changes projected for local climate drivers identified for the current scenario set, new global climate scenarios can be evaluated for the degree to which they would alter that range and therefore for the necessity of updating decisions associated with projected biological effects of climate change.</p>
<p>Optimism about climate-change scenarios</p> <p>Climate-change scenarios are climate predictions.</p> <p>Climate scientists can identify which scenarios are best or most likely.</p> <p>Climate-change scenarios define the range of plausible foreseeable outcomes.</p> <p>Climate-change scenarios with higher resolution are necessary, possible, and will improve ability to project biological effects.</p> <p>Uncertainties associated with climate-change scenarios will decrease in the near term, making them more useful for biological assessments.</p>	<p>Climate scientists carefully distinguish between climate projections, which are based on scenarios of future changes in climate forcings, and predictions (or forecasts), which attempt to simulate the actual climate state forward in time. Although the IPCC's 5th assessment report (AR5) will include results of climate-prediction experiments, the expected divergence of these decadal climate forecasts suggests the continued importance of evaluating a range of possible futures.</p> <p>Irreducible uncertainty about future greenhouse gas emissions, the fact that there is no single most reliable CM, and the confounding effect of natural variability mean it is impossible to determine the best, or most likely, climate-change scenario. The choice of the "best" scenario depends on the characteristics of the biological system of interest and the associated decision context (Table 1).</p> <p>Although scenarios indicating the least change seem well founded, the largest change scenario in CM archives does not necessarily represent the largest plausible future change. Managing for the worst case as identified by currently available scenarios may not be sufficient to guarantee resilience, and this should be clearly communicated to decision makers (step 3c).</p> <p>Not all aspects of the climate are simulated more accurately with higher resolution (e.g., Stock et al. 2010; Delworth et al. 2012). Development of higher resolution scenarios is limited by fine-scale data for validation of downscaled scenarios (Lundquist & Cayan 2007), especially in oceanic, aquatic, and mountainous environments, where much resource management is focused. Uncertainty regarding future climate changes is often not the primary factor limiting projections of future biological change (step 1).</p> <p>The IPCC AR5 is expected to increase uncertainty in estimates of climate change due to the increased complexity of current CMs (Knutti & Sedláček 2013). This suggests the need to identify climate-change scenarios that appropriately represent the range of projected outcomes (step 3) and improve understanding of biological linkages to climate so that ecological impact assessments can appropriately use the information provided by CMs (step 1).</p>

*Indicated steps refer to those in the guide for choosing and using scenarios, above.

divergence of these decadal climate forecasts suggests the continued importance of evaluating a range of possible futures.

Discussion

Our structured approach to choosing a salient and defensible subset of climate-change scenarios addresses a number of common (in our experience) misconceptions among practitioners regarding the utility of climate scenarios for decision making (Table 3). Our approach uses a bottom-up assessment of the climate sensitivity of the biological and resource management system to identify scenarios for use in the typical (top-down) impact assessment (Fig. 1) (Root & Schneider 1995). Despite directional uncertainty in some CM projections, robust scenarios of future conditions can be developed when biological effects are dominated by changes in other, better understood, variables.

Scenarios selected for ecological impact assessment should appropriately represent the range of projected conditions given the specific decision context for the analysis. Whether multiple emissions scenarios and ensemble members are considered (and if so, which ones) depends on the time horizon of analysis and the importance of natural variability. Our approach, which is similar to that used for assessing climate risks to water resources (Brown & Wilby 2012), demonstrates that the most appropriate scenarios for one impact assessment will not necessarily be the best for another because local climate drivers, biophysical linkages to climate, and decision characteristics may differ. However, the implications of new global climate scenarios for existing impact assessments can be rapidly evaluated based on how much they alter the range of projected changes or the magnitude of the relevant best- or worst-case scenario.

Developing a better understanding of the implications of climate change for biological systems, and for decision making, requires improved understanding of local biological linkages to climate, continued improvements in climate science, and better bridging of the gap between the climate and biological science communities. The lack of sufficiently detailed information on climate change is rarely the only, and seldom the most important, hurdle to assessing effects and implementing response strategies (Dessai et al. 2009). Predicting climate effects on ecosystems is as much of a challenge as predicting climate. Limited understanding of physical controls on biological systems typically results in even larger uncertainties in ecosystem effects than do uncertainties in future climate (Schindler et al. 2008). Clear identification of climate-information needs of the biological-science community, based on understanding of leading factors that affect local biological change, would help the climate-science community better align development, evaluation, and deliv-

ery of climate scenarios in support of ecological impact assessment and resource management efforts. Increased collaboration among climate scientists, biological scientists, and resource managers would advance the development of ecological impact assessments that reflect state-of-the-art understanding of both biological systems and climatic processes.

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Literature Cited

- Abatzoglou, J. T., and T. J. Brown. 2011. A comparison of statistical downscaling methods suited for wildfire applications. *International Journal of Climatology* 32:772–780.
- Annan, J. D., and J. C. Hargreaves. 2006. Using multiple observationally-based constraints to estimate climate sensitivity. *Geophysical Research Letters* 33.
- Auad, G., A. Miller, and E. Di Lorenzo. 2006. Long-term forecast of oceanic conditions off California and their biological implications. *Journal of Geophysical Research* 111.
- Baker, J. D., J. J. Polovina, and E. A. Howell. 2007. Effect of variable oceanic productivity on the survival of an upper trophic predator, the Hawaiian monk seal *Monachus schauinslandi*. *Marine Ecology Progress Series* 346:277–283.
- Battin, J., M. W. Wiley, M. H. Ruckelshaus, R. N. Palmer, E. Korb, K. K. Bartz, and H. Imaki. 2007. Projected impacts of climate change on salmon habitat restoration. *Proceedings of the National Academy of Sciences* 104:6720–6725.
- Beer, W. N., and J. J. Anderson. 2011. Sensitivity of juvenile salmonid growth to future climate trends. *River Research and Applications* 27:663–669.
- Brainard, R., C. Birkeland, C. Eakin, P. McElhany, M. Miller, M. Patterson, G. Piniak, M. Dunlap, and M. Weijerman. 2013. Incorporating climate change and ocean acidification into 368 extinction risk assessments for 82 coral species. *Conservation Biology* 27:1169–1178.
- Boughton, D., and A. Pike. 2013. Floodplain rehabilitation as a hedge against hydroclimate uncertainty in a threatened steelhead migration corridor. *Conservation Biology* 27:1158–1168.
- Brown, C. J., et al. 2011. Quantitative approaches in climate change ecology. *Global Change Biology* 17:3697–3713.
- Brown, C., and R. L. Wilby. 2012. An alternative approach to assessing climate risks. *Eos Transactions, American Geophysical Union* 93:401–402.
- Burger, G., T. Q. Murdock, A. T. Werner, S. R. Sobie, and A. J. Cannon. 2012. Downscaling extremes—an intercomparison of multiple statistical methods for present climate. *Journal of Climate* 25:4366–4388.
- Busch, D. E., and J. C. Trexler. 2003. *Monitoring ecosystems: interdisciplinary approaches for evaluating ecoregional initiatives*. Island Press, Washington, D.C.
- Delworth, T., et al. 2012. Simulated climate and climate change in the GFDL CM2.5 high-resolution coupled climate model. *Journal of Climate* 25:2755–2781.

- Deser, C., R. Knutti, S. Solomon, and A. S. Phillips. 2012a. Communication of the role of natural variability in future North American climate. *Nature Climate Change* **2**:775–779.
- Deser, C., A. S. Phillips, V. Bourdette, and H. Teng. 2012b. Uncertainty in climate change projections: the role of internal variability. *Climate Dynamics* **38**:527–546.
- Dessai, S., M. Hulme, R. Lempert, and R. Pielke Jr. 2009. Do we need more precise and accurate predictions in order to adapt to a changing climate? *Eos Transactions, American Geophysical Union* **90**:111–112.
- Dettinger, M. D., et al. 2011. Design and quantification of an extreme winter storm scenario for emergency preparedness and planning exercises in California. *Natural Hazards* **60**:1085–1111.
- Fogarty, M. J., L. Incze, K. Hayhoe, D. G. Mountain, and J. Manning. 2008. Potential climate change impacts on Atlantic cod (*Gadus morhua*) off the northeastern USA. *Mitigation and Adaptation Strategies for Global Change* **13**:453–466.
- Fowler, H. J., S. Blenkinsop, and C. Tebaldi. 2007. Linking climate change modelling to impacts studies: recent advances in downscaling techniques for hydrological modelling. *International Journal of Climatology* **27**:1547–1578.
- Hare, J. A., M. A. Alexander, M. J. Fogarty, E. H. Williams, and J. D. Scott. 2010. Forecasting the dynamics of a coastal fishery species using a coupled climate–population model. *Ecological Applications* **20**:452–464.
- Hare, J. A., et al. 2012. Cusk (*Brosme brosme*) and climate change: assessing the threat to a data poor candidate species under the Endangered Species Act. *ICES Journal of Marine Science* **69**:1753–1768.
- Hazen, E. L., et al. 2013. Predicted habitat shifts of Pacific top predators in a changing climate. *Nature Climate Change* **3**:234–238.
- Hoegh-Guldberg, O., J. C. Ortiz, and S. Dove. 2011. The future of coral reefs. *Science* **334**:1494–1495.
- IPCC (Intergovernmental Panel on Climate Change). 2007. Climate change 2007: the physical science basis. Contribution of Working Group I to S. Solomon, D. Qin, M. Manning, Z. Chen, M. Marquis, K. B. Averyt, M. Tignor, and H. L. Miller, editors. The fourth assessment report of the intergovernmental panel on climate change. Cambridge University Press, Cambridge, United Kingdom.
- King, J. R., V. N. Agostini, C. J. Harvey, G. A. McFarlane, M. G. G. Foreman, J. E. Overland, E. Di Lorenzo, N. A. Bond, and K. Y. Aydin. 2011. Climate forcing and the California Current ecosystem. *ICES Journal of Marine Science* **68**:1199–1216.
- Knutti, R. 2008. Should we believe model predictions of future climate change? Triennial Issue Earth Science of Philosophical Transactions of the Royal Society **366**:4647–4664.
- Knutti, R. 2010. The end of model democracy? Editorial for *Climatic Change* **102**:395–404.
- Knutti, R., R. Furrer, C. Tebaldi, J. Cermak, and G. A. Meehl. 2010. Challenges in combining projections from multiple models. *Journal of Climate* **23**:2739–2758.
- Knutti, R., and J. Sedláček. 2013. Robustness and uncertainties in the new CMIP5 climate model projections. *Nature Climate Change* **3**:369–373.
- Littell, J. S., and R. Gwozdz. 2011. Climatic water balance and regional fire years in the Pacific Northwest, USA: linking regional climate and fire at landscape scales. Pages 117–139 in D. McKenzie, C. M. Miller, and D. A. Falk, editors. *The landscape ecology of fire: ecological studies*. Springer, The Netherlands.
- Littell, J. S., D. McKenzie, B. K. Kerns, S. Cushman, and C. G. Shaw. 2011. Managing uncertainty in climate-driven ecological models to inform adaptation to climate change. *Ecosphere* **2**. DOI: 10.1890/ES11-00114.1.
- Lundquist, J. D., and D. R. Cayan. 2007. Surface temperature patterns in complex terrain: daily variations and long-term change in the central Sierra Nevada, California. *Journal of Geophysical Research* **112**.
- Mantua, N. J., S. R. Hare, Y. Zhang, J. M. Wallace, and R. C. Francis. 1997. A Pacific interdecadal climate oscillation with impacts on salmon production. *Bulletin of the American Meteorological Society* **78**:1069–1079.
- Margoluis, R., C. Stem, N. Salafsky, and M. Brown. 2009. Using conceptual models as a planning and evaluation tool in conservation. *Evaluation and Program Planning* **32**:138–147.
- Maurer, E. P., L. D. Brekke, and T. Pruitt. 2010. Contrasting lumped and distributed hydrology models for estimating climate change impacts on California watersheds. *Journal of the American Water Resources Association* **46**:1024–1035.
- Maurer, E. P., L. Brekke, T. Pruitt, and P. B. Duffy. 2007. Fine-resolution climate projections enhance regional climate change impact studies. *Eos Transactions, American Geophysical Union* **88**:504.
- Maurer, E. P., and H. G. Hidalgo. 2008. Utility of daily vs. monthly large-scale climate data: an intercomparison of two statistical downscaling methods. *Hydrology and Earth System Sciences* **12**:551–563.
- McAfee, S. A., J. L. Russell, and P. J. Goodman. 2011. Evaluating IPCC AR4 cool-season precipitation simulations and projections for impacts assessment over North America. *Climate Dynamics* **37**:2271–2287.
- McClure, M. M., et al. 2013. Incorporating climate science in applications of the U.S. Endangered Species Act for aquatic species. *Conservation Biology* **27**:1222–1233.
- McCullough, D. A. 1999. A review and synthesis of effects of alterations to the water temperature regime on freshwater life stages of salmonids, with special reference to Chinook salmon. *Water resources assessment* 910-R-99-010. U.S. Environmental Protection Agency, Seattle.
- McKelvey, K. S., J. P. Copeland, M. K. Schwartz, J. S. Littell, K. B. Aubry, J. R. Squires, S. A. Parks, M. M. Elsner, and G. S. Mauger. 2011. Climate change predicted to shift wolverine distributions, connectivity, and dispersal corridors. *Ecological Applications* **21**:2882–2897.
- Meehl, G., et al. 2007. IPCC standard output from coupled ocean-atmosphere GCMs. Lawrence Livermore National Laboratory Program for Climate Model Diagnosis and Intercomparison, Livermore, California. Available from http://www-pcmdi.llnl.gov/ipcc/standard_output.html#overview (accessed May 2013).
- MIT (Massachusetts Institute of Technology) Joint Program on the Science and Policy of Global Change. 2012. 2012 Energy and climate outlook. MIT, Cambridge, Massachusetts.
- Moss, R. H., et al. 2010. The next generation of scenarios for climate change research and assessment. *Nature* **463**:747–756.
- Mote, P. W., L. Brekke, P. Duffy, and E. Maurer. 2011. Guidelines for constructing climate scenarios. *Eos Transactions, American Geophysical Union* **92**:257–258.
- Mote, P. W., and E. P. Salathé. 2010. Future climate in the Pacific Northwest. *Climatic Change* **102**:29–50.
- Nakicenovic, N., et al. 2000. Intergovernmental panel on climate change special report on emissions scenarios. Cambridge University Press, Cambridge, United Kingdom.
- NOAA (National Oceanic and Atmospheric Administration). 2010. Next generation strategic plan. NOAA, Silver Spring, Maryland.
- Oldenborgh, G. J. van, F. J. Doblas-Reyes, B. Wouters, and W. Hazeleger. 2012. Skill in the trend and internal variability in a multi-model decadal prediction ensemble. *Climate Dynamics* **38**:1263–1280.
- Overland, J. E., and M. Wang. 2007. Future climate of the North Pacific Ocean. *Eos Transactions, American Geophysical Union* **88**:178–182.
- Overland, J. E., M. Wang, N. A. Bond, J. E. Walsh, V. M. Kattsov, W. L. Chapman. 2011. Considerations in the selection of global climate models for regional climate projections: the Arctic as a case study. *Journal of Climate* **24**:1583–1597.
- Peters G., G. Marland, C. Le Quééré, T. Boden, J. G. Canadell, and R. R. Raupach. 2012. CO2 emissions rebound after the global financial Crisis. *Nature Climate Change* **2**:2–4.

- Pierce, D. W., T. P. Barnett, B. D. Santer, and P. J. Gleckler. 2009. Selecting global climate models for regional climate change studies. *Proceedings of the National Academy of Sciences of the U.S.A.* **106**:8441–8446.
- Pierce, D. W., et al. 2013. Probabilistic estimates of future changes in California temperature and precipitation using statistical and dynamical downscaling. *Climate Dynamics* **40**:839–856.
- Pohlmann, H., J. Jungclaus, A. Köhl, D. Stammer, and J. Marotzke. 2009. Initializing decadal climate predictions with the GECCO oceanic synthesis: effects on the North Atlantic. *Journal of Climate* **22**:3926–3938.
- Roe, G. H., and K. C. Armour. 2011. How sensitive is climate sensitivity? *Geophysical Research Letters* **38**.
- Root, T. L., and S. H. Schneider. 1995. Ecology and climate: research strategies and implications. *Science* **269**:334–341.
- Salathé, E. P., L. R. Leung, Y. Qian, and Y. Zhang. 2010. Regional climate model projections for the State of Washington. *Climatic Change* **102**:51–75.
- Salathé E. P., P. W. Mote, and M. W. Wiley. 2007. Review of scenario selection and downscaling methods for the assessment of climate change impacts on hydrology in the United States Pacific Northwest. *International Journal of Climatology* **27**:1611–1621.
- Schindler, D. E., X. Augerot, E. Fleishman, N. J. Mantua, B. Riddell, M. Ruckelshaus, J. Seeb, and M. Webster. 2008. Climate change, ecosystem impacts, and management for Pacific salmon. *Fisheries* **33**:502–506.
- Stock, C. A. et al., 2010. On the use of IPCC-class models to assess the impact of climate on living marine resources. *Progress in Oceanography* **88**:1–27.
- Solomon, A., et al. 2011. Distinguishing the roles of natural and anthropogenically forced decadal climate variability: implications for prediction. *Bulletin of the American Meteorological Society* **92** DOI: <http://dx.doi.org/10.1175/2010BAMS2962.1>.
- Taylor, K. E., R. J. Stouffer, and G. A. Meehl. 2012. An overview of CMIP5 and the experiment design. *Bulletin of the American Meteorological Society* **93**:485–498.
- USDOI (U.S. Department of Interior). 2009. Climate change and the Department of Interior. Secretarial order 3226, amendment no. 1. USDOI, Washington, D.C.
- USFS (U.S. Forest Service). 2010. National roadmap for responding to climate change. USFS, Washington, D.C.
- Van Houtan, K. S., and J. M. Halley. 2011. Long-term climate forcing in loggerhead sea turtle nesting. *Public Library of Science ONE* **6**:e19043.
- Walsh, J., W. L. Chapman, V. Romanovsky, J. H. Christensen, and M. Stendel. 2008. Global climate model performance over Alaska and Greenland. *Journal of Climate* **21**:6156–6174.
- Walters, A., K. Bartz, and M. McClure. 2013. Interactive effects of water diversion and climate change for juvenile Chinook salmon in the Lemhi River Basin (U.S.A.). *Conservation Biology* **27**:1179–1189.
- Wang, M., J. E. Overland, and N. A. Bond. 2010. Climate projections for selected large marine ecosystems. *Journal of Marine Systems* **79**:258–266.
- Weeks, D., P. Malone, and L. Welling. 2011. Climate change scenario planning: a tool for managing parks into uncertain futures. *Park Science* **28**:26–33.
- Wenger, S. J. et al. 2011. Flow regime, temperature and biotic interactions drive differential declines of trout species under climate change. *Proceedings of the National Academy of Sciences* **108**:14175–14180.
- Wood, A. W., L. R. Leung, V. Sridhar, and D. P. Lettenmaier. 2004. Hydrologic implications of dynamical and statistical approaches to downscaling climate model outputs. *Climatic Change* **62**:189–216.
- Yang, X., et al. 2013. A predictable AMO-like pattern in the GFDL fully coupled ensemble initialization and decadal forecasting system. *Journal of Climate* **26**:650–661.

