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Managing uncertainty in climate-driven ecological models to inform adaptation to climate change

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Abstract. The impacts of climate change on forest ecosystems are likely to require changes in forest planning and natural resource management. Changes in tree growth, disturbance extent and intensity, and eventually species distributions are expected. In natural resource management and planning, ecosystem models are typically used to provide a "best estimate" about how forests might work in the future and thus guide decision-making. Ecosystem models can be used to develop forest management strategies that anticipate these changes, but limited experience with models and model output is a challenge for managers in thinking about how to address potential effects of climate change. What do decision makers need to know about climate models, ecological models used for impacts assessments, and the uncertainty in model projections in order to use model output in strategies for adaptation to climate change? We present approaches for understanding and reducing the uncertainty associated with modeling the effects of climate change on ecosystems, focusing on multi-model approaches to clarify the strengths and limits of projections and minimize vulnerability to undesirable consequences of climate change. Scientific uncertainties about changes in climate or projections of their impacts on resources do not present fundamental barriers to management and adaptation to climate change. Instead, many of these uncertainties can be controlled by characterizing their effects on models and future projections from those models. There is uncertainty in decision making that does not derive just from the complex interaction of climate and ecosystem models, but in how modeling is integrated with other aspects of the decision environment such as choice of objectives, monitoring, and approach to assessment. Adaptive management provides a hedge against uncertainty, such that climate and ecosystem models can inform decision making.

Key words: adaptation; climate change; climate models, decision making under uncertainty; empirical models; landscape models; process models; uncertainty; vegetation models.

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Introduction

Natural resource management will change in the 21st century because climate change is impacting many components of ecosystems, often in novel and surprising ways (Millar et al. 2007, Joyce et al. 2008, Blate et al. 2009, Littell et al. 2011*a*). Likely forest ecosystem changes driven at least partially by climate include: biogeographic range shifts for species (Rehfeldt et al. 2006) including invasives; changes in plant communities as individual species form new assemblages (e.g., Davis 1986); changes in disturbance regimes, including fire (Littell et al. 2009, Littell et al. 2010), insects (Hicke et al. 2006), and diseases and pathogens (Lovett et al. 2006); and changes in hydrology (e.g., Tague et al. 2009) and biogeochemical cycling (e.g., Campbell et al. 2009). These "new" ecosystems will have structure, disturbance interactions, and functions outside the historical frame of reference. These differences will require rethinking what processes can be affected, how they are managed, and what can be expected of forest ecosystem services (Millar et al. 2007, Bosworth et al. 2008) when past experience is limited as a guide to future conditions. For example, management strategies based on static plant associations, historical ecosystem processes, or historical disturbance regimes are unlikely to be compatible with the trajectory of future ecosystems (Millar and Woolfenden 1999, Joyce et al. 2008, Blate et al. 2009, Lawler 2009, Lawler et al. 2010, Littell et al. 2011*a*).

Resource management goals will likely change as well; which resources and services to emphasize may differ under climate change. Future strategies for managing timber, water, biodiversity, recreation, and other ecosystem services will need to accommodate climatically driven changes to the resource base, the ability of management to influence that resource base, new demands of stakeholders for ecosystem services, and interactions with other stressors. For example, in some ecosystems, timber resources may be less predictable under changing disturbance regimes and climatically altered habitat (Churkina and Running 2000, Littell et al. 2010). Similarly, endemic species existing near thresholds or within narrow environmental tolerances, such as cold water fish (Mantua et al. 2010), pikas (Morrison and Hik 2007), and wolverines (Aubry et al. 2007), will experience climatic conditions outside their suitable range more frequently, leading to increased stress. Some species, including some invasives, will be physiologically favored by a warming CO_2-rich world (Dukes and Mooney 1999), impacting other species that may or may not be so favored.

Given these potential futures, projecting ecological impacts and planning for their consequences are critical to decision making and adaptation to climate change (e.g., Fankhauser et al. 1999, Hulme 2005, Millar et al. 2007, Snover et al. 2007). Clearly all adaptation—and resilience—depends on local action to adapt to global climate change and regional vulnerability of people and resources. Institutions must move from an emphasis on conceptual adaptation to action (Vogel et al. 2007), but the prospect of anticipating future climate change impacts and prioritizing and executing natural resource management is daunting. The frames of reference that guide decision-making are limited in that for decades, resource managers and planners have used past conditions and processes to frame management and restoration of resilient ecosystems. However, the observed past (historic range of variability, stationarity) is not likely to be a reliable guide because the future, perhaps even the near future, will experience different climatic dynamics and disturbance interactions (e.g., Frederick et al. 1997, Milly et al. 2008, Millar et al. 2007).

In natural resource planning, models are typically used to predict how resource dynamics will unfold in the future and to guide decision-making. The role of models in this context is not to predict the future exactly, but rather to narrow its possible range to a subset of plausible outcomes that identify the vulnerability of specific resources and suggest appropriate management. However, the utility of future climate-driven ecological projections is often questioned by managers and decision makers, because issues arise that are outside their experience. Limited experience with models and model output has been identified as a challenge for managers in thinking about how to anticipate climate change (Littell et al. 2011*a*). One of the largest barriers is the complexity of climate and ecosystem models and the uncertainties that arise when they are linked. In this paper, we focus on this linkage and explore how its uncertainties affect decision making in natural resources. We discuss (1) the strengths and limits of ecosystem models per se, using vegetation models as an example, (2) climate model selection and relationships to ecosystem models, (3) using model output to reduce uncertainty and mitigate impacts, and (4) using model output to make decisions with known risks. We build on results from a pair of workshops (Robinson et al. 2008, and "Climate change, vegetation models, and decision making in the face of uncertainty," June 2–3, 2008, Denver, CO, ⟨http://www.forestryvideos.net/series/climate-change-vegetation-models-and-decision-making-in-the-face-of-uncertainty⟩).

Ecosystem Impacts Models

There are important differences among the ecological models that might be used to predict the effects of climate change, partly because few ecosystem models were developed initially for that express purpose. There are strengths and limitations common to all models, and the differences are in some cases a matter of degree, stemming from tradeoffs made in model development, but in other cases they are fundamental, particularly when it comes to how climate is incorporated in the model. All models are simplifications of reality with the intent to capture the necessary and sufficient dynamics, often with only the minimum required components. This is both a strength and a limitation—models pare the "real world" down to its most important constituents, but in doing so sacrifice real-world detail and assume that un-incorporated processes are less important. Despite this simplification, however, most models are not transparent to users and in many cases are still too complex for the average user, who is less aware of a model's specific limitations, to diagnose and assess.

Using an ensemble of models, as climate impacts modelers do (see *Climate model selection . . .: Ensemble modeling*), can reduce uncertainty, but it may increase uncertainty if the models produce contradictory output, or if the models are too similar (and not truly independent) they may produce similar output that does not reflect the true variability. Even in that worst-case scenario, however, multi-model analyses can still help define the scope of uncertainty and in some cases its key sources, such as the role of CO_2 fertilization in dynamic global vegetation models (e.g., Lenihan et al. 2008), or the absence of disturbance in statistical species models (Guisan and Thuiller 2005). As with many systems models, one of their primary uses is identifying research and monitoring needs (Thrush et al. 2009). Multi-model analysis may not be easy, or even feasible, if constituent models run at different spatial or temporal scales. Scale is a key consideration in making global climate projections relevant to ecosystem models (Wiens and Bachelet 2010), and choices of the scale at which interactions between the two are represented, and of downscaling methodology, affect the type and magnitude of uncertainty in projections. Similarly, "outlier" models may actually incorporate important processes or interactions that make them superior to many models that agree and do not include the same process. Therefore, when it comes to assessing uncertainty, it is as important—if not more important—to attempt to understand why disagreement occurs as it is to understand why there may be agreement (Rastetter 1996).

Example: vegetation models

Vegetation models often incorporate climate explicitly, because the link between climate and vegetation is strong. Some vegetation models' development may predate the current research focus on climate change, so they should not be regarded primarily as "climate impact models" or "climate change models". A notable exception is Dynamic Global Vegetation models (DGVMs; Table 1).

Vegetation models are of two primary types: (1) empirical (statistical), (2) process or mechanistic (Table 1). Empirical models fit parameters to observations and use statistical methods to make projections. They are common in research and management and are generally relatively easy to use. Evaluation/validation of empirical models is tractable using numerical methods (e.g., cross validation) and quantifies uncertainty routinely, but it is difficult for them to extrapolate to novel conditions or account for complex interactions. Process models are built from "first principles", are generally more difficult to use,

Table 1. Some vegetation model strengths and limitations by class, after Robinson et al. 2008.

Model Type	Strengths	Limitations
Statistical Species Models (e.g., McKenzie et al. 2003, Hamann and Wang 2006, Rehfeldt et al. 2006, 2008, Iverson et al. 2008)	Quantitative relationships between climate variables and species distributions are frequently obvious and conceptually simple	Many methods, some numerically complex and not easy to use, not obvious which methods are best
	Many models to select from with readily available computer software packages	Models provide a climate-equilibrium assessment whereas climate change requires transient approach
	Parameter estimation is fully quantitative	No explicit representation of ecological interactions (e.g., competition, disturbance)
	Explicit climate incorporation	Novel climates typically interpreted as unsuitable for species – this assumption may be false.
	Provide range maps at any scale of biological organization (species, vegetation types)—dependent on data used for model construction	For long lived species, distributions can predate the observed climate data—climatic attribution is uncertain
	Can be used to identify geographic locations of species vulnerability; can be linked to landscape models.	Can be difficult to use and learn
Process Models: Gap (e.g., Botkin et al. 1972, Bugmann 2001)	Can be used at stand levels and incorporate stand-level disturbance	Limited spatial scale application
	Can be linked to spatially-explicit landscape scale models	Require local calibration; limits broad use by managers
	Include physiological processes that can be linked to climate drivers explicitly	Most not spatially explicit
	Model structure is flexible	Ecophysiology is limited compared to biogeochemical models
	Individual tree level provides detailed response applicable to management problems	Work well in forests, poorly at forest ecotones
	Relative to statistical models they can be more robust to prediction given their basis in known mechanisms	Growth limiting factors differ regionally; may reflect developers bias—no general formulation (but FORCLIM represents some progress)
	Limiting factors (e.g., temperature, precipitation) follow mechanistic process equations and provide a deterministic representation of ecological process	CO_2 interactions with vegetation not explicitly represented in most existing models
		Can be difficult to use and learn
Process Models: Biogeochemical (e.g., Campbell et al. 2009)	Track multiple temperature and precipitation controlled processes (e.g., hydrology, gas exchange) in forests and account for their interactions	Based on functional types rather than species
	Explicit climate incorporation	Variables used by managers (e.g., stand structure) are not available or are limited
	Carbon budgets are a natural component	Sensitive to downscaling: different processes operate at very small scales (applies to other model classes as well)
	Ecosystem process focus makes them flexible for different vegetation types	Difficult to use and learn
	Can identify process- and rate-limiting factors in different regions	
Process Models: Dynamic Global Vegetation Model (e.g., dynamic models Cramer et al. 2001, Lenihan et al. 2008, equilibrium models Melillo et al. 1995, Neilson 1995)	Based on physiological mechanisms or relationships	Based on functional types rather than species

Table 1. Continued.

Model Type	Strengths	Limitations
	Sensitive to changes in CO_2, H_2O and temperature	Variables used by managers (e.g., stand structure) are not available or are limited
	Applicable to forest and non-forest settings	Computationally intensive, difficult to use and learn
	Can identify process, rate, and structural limiting factors in different regions	Use is highly dependent on model developers/experts
	Explicit climate incorporation	Usually not down-scaled to the spatial level useful to managers; e.g., 10 km^2 result may not capture details such as microsite refugia
	Mechanistic nature allows novel climates to be incorporated.	If downscaled data are used, processes modeled may not match spatial scale
Landscape Models (e.g., He et al. 2002, Keane et al. 2004)	Most have explicit representation of multiple spatial processes	Some models have limited mechanistic approach
	Climate incorporation can be explicit, but often is not	Multiple scales of interactions difficult to model well—data dependent
	Can encompass the strengths of gap models within each cell if processes embedded	Data intensive: spatially explicit requirements
	Many available models to select from, for different applications	Steep learning curve for use
	If spatial data are available, easily adaptable to forest and non-forest settings at multiple scales	Some are highly dependent on model developers/experts
	Can explore links across different scales from local to landscape	
	Scale can be flexibly tailored for most management use and applications	
Vegetation Models in General (e.g., Cushman et al. 2007)	Model construction and development history often with vegetation prediction and/or projection in mind	Insects, herbivores rarely included. Depending on scale of interest and insect, this can limit analyses of multiple stressors
	Multiple climatic, hydrologic, and ecological processes can be coupled to emulate forests and their disturbances in a spatially explicit framework	Invasive species rarely included; depending on scale of interest, ecosystem, and invasive, this can limit analyses of multiple stressors
		Land use change and management actions not often explicitly accounted for
		Transient effects of climate change and climate variability are not always possible to predict when existing but un-modeled thresholds and nonlinearities are not included

and not so commonly used in management. They are more limited than empirical models in quantifying uncertainty (but see Turley and Ford 2009), but can incorporate complex and novel interactions and, to the extent they are modular, be adapted to more general or specific purposes. There is often considerable debate among modelers regarding which approach is "better." Both model classes have strengths and limitations (Table 1), and choosing one approach over the other depends greatly on matching processes and parameters to objectives of research and management. It is also possible—even desirable—to use these two approaches in conjunction. Moreover, as vegetation models evolve in response to the complexities of incorporating climate change, the distinction between "empirical" and "process" models may become less clear. Data assimilation techniques (e.g., Luo et al. 2009) also make it possible to calibrate a mechanistic model to observed data, blurring the distinction further. Distributed hydrologic modeling, for example, often calibrates a mechanistic hydrologic model to observed streamflow (e.g., Elsner et al. 2010).

Either empirical or mechanistic models can be placed in a spatial (and often contagion) context to develop landscape models, which then extend empirical or mechanistic models (or elements of both) to explicit simulation of ecological processes in space (Cushman et al. 2007). Landscape models that address contagion (process interaction across cells) are especially suited to simulations of the effects of disturbance on vegetation. They typically use climate information as inputs (e.g., for probabilistic fire simulation, Keane et al. 1999, He et al. 2002), but climate is not always incorporated explicitly for simulating ecosystem processes in landscape models.

Climate Model Selection and Relationship to Ecosystem Models

In any particular region, many locally or regionally specific climate datasets or future climate projections may be available. If there are several options for generating climate inputs to an ecosystem model, then how does one choose which climate projections to use? There are several things to consider when multiple products are available, including (1) what are the objectives of modeling, (2) how many and which models should one use, (3) what spatial and temporal scales of information are needed and available, and (4) whether climate model output can be coupled to ecosystem models.

Ensemble modeling

Regional climate projections can currently be derived from more than twenty different global climate models (GCMs). These GCMs have different representations of interactions among the land surface, ocean, atmosphere, and sea ice, different inherent physics, and different assumptions about the climate system's sensitivity to forcing. To project future climate, GCMs are all "forced" in part with in-common scenarios of greenhouse gas emissions, which make different assumptions about future economic activity and fossil fuel use (Nakicenovic et al. 2000). The number of GCMs that use each scenario varies as does the number of realizations of each climate model for a given scenario, although there are many models that use the B1, A1B, and A2 scenarios through 2100. The differences in climate and thus impacts between these emission scenarios do not strongly diverge until middle or late 21st century (Nakicenovic et al. 2000). Selection of climate input data for an ecosystem model therefore involves choosing both a GCM and an emission scenario. "Ensembles", or groups of several climate models, can constrain estimates of uncertainty in climate projections for a region (Pierce et al. 2009), and can help evaluate which models have the best fidelity to 20th century observations (e.g., Mote and Salathe 2010). Ideally, results from multiple GCMs would be input climate for a given ecosystem model so that the range of future climate projections and their consequences for ecosystem impacts could be evaluated, but this is computationally intensive. The large number of possibilities (not all of which are necessarily equally likely) and the associated database storage and programming issues, limit the feasibility of this approach for most end users. A common solution in such cases is to use the mean of multiple GCMs or the "ensemble mean" for a particular emissions scenario (Fig. 1). The ensemble-mean approach is often superior to any single model for estimating mean climate (Pierce et al. 2009), because it reduces the influence of natural internal climate variability in any single model and also reduces the influence of any "error" in an individual model's parameters. One can also limit the membership of the ensemble to models that perform best in a current region (Mote and Salathé 2010), with the assumption that those models have internal physics that render them superior in that region, and then weight the models by their fidelity to observations. It is worth noting that it is possible that one or more of the eliminated models could have dynamics that cause it to perform poorly when tested against the historical record, but, by chance, a change in natural interactions in the future would cause it to perform better than others in the future. This would only be true if the processes excluded from skillful models became more important than included processes. However, there would be no way to know this a priori except in the case that such differences had a theoretical scientific root.

The ensemble mean approach may not be

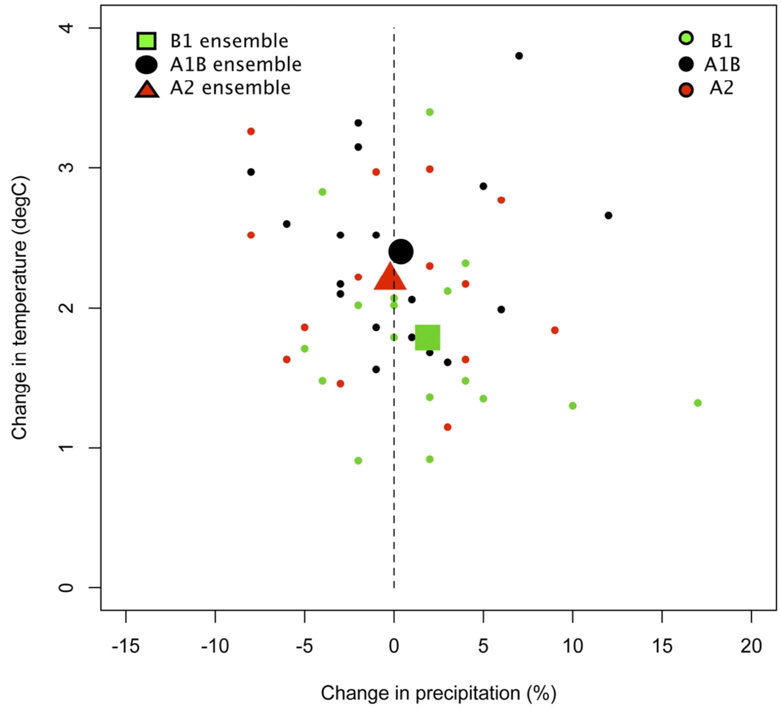

Fig. 1. Ensemble means and model variation across GCMs for changes in precipitation and temperature over the Colorado River Basin between the reference period (1970–1999) and the 2040s (2030–2059), under three SRES socio-economic scenarios. Values for the Colorado River Basin were extracted from global model output, after Littell et al. (2011*b*).

sufficiently robust because of two sources of variability: the natural variability in the climate system, and in uncertainty in climate-model parameters such as model sensitivity to radiative forcing or feedbacks such as the change in albedo from loss of sea ice. The effects of future climate, particularly at scales relevant to management and adaptation, may be associated with departures from mean conditions (i.e., extremes) rather than future means (Knutti 2008, Dessai et al. 2009). The most robust approach for adaptation may be to start with the ensemble mean and "move outward", using a range of future scenarios to bracket future conditions. Adaptation strategies taking this range into account acknowledge that the variation in outcomes is part of the decision process (Dessai et al. 2009). For example, contrasting the ecosystem impacts from climate models that project warmer drier future conditions versus those that project warmer wetter conditions might provide a range of future scenarios useful for examining future fire regimes or net ecosystem productivity, whereas the ensemble mean would give little insight into this range of outcomes. Unfortunately, this approach does little to decrease uncertainty surrounding processes that are driven primarily by extremes, whose modeling is much more difficult, requiring either assumptions about the nature of change in the tails of distributions or the use of dynamic regional climate models.

Another way to further narrow the number of ensemble members is to pair emissions scenarios based on a gradient of risk (Kerns et al. 2009, Mote and Salathé 2010). For example, high emissions scenarios paired with more sensitive (warmer) GCMs represent a set of higher impact scenarios for many forest processes—planning for these is risk averse. Lower emissions scenarios paired with models that project less warming lead to lower impact scenarios—planning for these is risk tolerant.

Reconciling spatial and temporal scales

Global climate models typically make projections on grids at resolutions of thousands or tens of thousands of square kilometers, with each cell representing a sort of "average" condition within its boundaries. There is a scale mismatch with the needs of land managers who deal with spatial variation in actual climate caused by local and regional topography, and depending on decision-making objectives, it could be counterproductive to assume that global-model cell averages apply uniformly across landscapes. Similarly, much of the easily accessible global climate model output is archived in monthly time steps, whereas process-based ecosystem models often run at daily or even hourly time steps. The techniques of "downscaling" and "disaggregation" attempt to address these mismatches in scale.

Downscaling uses local information, usually topography and interpolated observations of temperature and precipitation, to adjust global climate model output to finer resolution (Wood et al. 2002, Salathé 2003, Wood et al. 2004, Salathe et al. 2007). The simplest method of downscaling, often called the "delta method", modifies observed historical climate data by adding or subtracting projected changes in temperature and precipitation derived from global models over the region of interest. A more sophisticated approach is statistical downscaling, which develops more complex quantitative relationships between global modeled climate and finer-scale observed climate. This statistical relationship is then projected into the future, assuming that the relationship between the global climate (and its variation) and the local climate (and its variation) is constant. Both methods rely on the historical record for their spatial structure, but some statistical downscaling methods get their temporal variability from the GCMs, some from the historical record, and some from both. Medium-scale dynamics, such as orographic effects of smaller mountain ranges, limit the power of statistical downscaling. Consequently, interactions between future atmospheric variability and land surfaces will be poorly constrained. For example, some places may warm faster or slower than the regional average, due to influences like sub-regional changes in snow albedo feedback (e.g., Salathé et al. 2010).

Dynamical downscaling, or regional climate modeling, sidesteps this limitation by using the global climate model only to generate boundary conditions. These are then used to drive a regional weather model that can make projections at finer spatial (e.g., 12 km or less) and temporal scales than GCMs and simulate more realistic variation in atmospheric changes and local feedbacks associated with topography, snow, and vegetation (Salathé et al. 2010, Duliere et al. 2011). This approach is much more computationally intensive than statistical downscaling, but it can also highlight sub-regional differences in topographically or physically driven responses to climate change. A further advantage of dynamical downscaling is that extreme events (floods, extreme precipitation events, cold snaps, or heat waves) outside the range of historical observations emerge directly from model dynamics. In contrast, statistical downscaling can generate these extreme events only by somewhat artificial procedures such as quantile mapping (e.g., Hamlet et al. 2010). Changes in extremes are important for ecosystem modelers; for example, in predicting changes in tree mortality (Allen and Breshears 1998) or area burned by wildfire (Strauss et al. 1989).

Disaggregation is the temporal analogue to downscaling. For example, for applications that require daily or hourly weather input, disaggregation can use observed monthly distributions of precipitation or temperature to generate synthetic time series of weather variables consistent with selected statistical properties of an observed month, but with the climatic drivers supplied by the downscaled future climate (Salathé et al. 2007). This process assumes that these statistical properties will be roughly approximated in the future (Salathé 2005).

Finer-scale climate projections are not always better. Just because a finer scale has been achieved does not mean the projections are more realistic or more consistent with the underlying physics. For example, downscaling can over-resolve the information in GCMs (or the observational record, in the case of sparse stations) and create false precision and a false sense of confidence. Detailed information on the interaction of local conditions and regional climate is necessary to corroborate this confidence. On the other hand, there may be useful information for ecosystem models in the difference between a regional climate projection and a localized estimate based on interpolation and physical variation. Two questions for users to ask are: "Are finer downscaled projections based on finer (and more local) observations needed, and if so, do they capture the local variation between units (e.g., 800 m pixels)?" "Are they worth the cost and potential false precision (in the absence of observations about such fine-scale variability) given the reality of sparse observations?" If climate information is available or realistic only at coarse scales, then decision making may need to incorporate the mismatch in scale by including the heterogeneity of responses within a larger-scale climate projection.

Linking climate and ecosystem models

Climate information can be incorporated into ecosystem models in two ways. One is "climate explicit", in which climate is a direct predictor of an ecosystem response. The other is "climate implicit", in which the ecosystem response is inferred using some surrogate factor (e.g., site index, elevation, or latitude/longitude) that is itself partially related to climate. With the increasing availability of gridded climate data, both observed and modeled, the implicit approach is rightly falling out of favor. In climate-explicit models, ecosystem responses are directly a function of climate variables, their interactions, and their role in other processes affecting vegetation, such as disturbance. Direct relationships between climate and ecosystem gradients are desirable, and are one way to reduce uncertainty in projections based on false assumptions about causation vs. correlation (Cushman et al. 2007).

Matching scales between climate outputs and ecosystem models helps control uncertainty. If a scale mismatch exists, understanding the implications for future projections is one component of diagnosing the uncertainty associated with the projection. Locally specific models with highly specific data are sometimes required to address a resource question, but other times a general conclusion from a broader scale will suffice and even be superior from an uncertainty standpoint, particularly when downscaling would exceed the resolution supported by observations. A *regional focus* on climate, planning, and adaptation prioritizes efforts at a level where climate model output is most robust. The question of which GCMs to choose for projections is tractable at regional levels, because seasonal cycles and sensitivity to climate variability often have recognizable regional-scale features that interact with regional ecosystem resources. Understanding local influences on climate may be required for projection of certain resource impacts, but as discussed above, using finer-scale data is not always better.

We can now frame the questions from the beginning of this section more explicitly. When choosing climate data to use for adaptation, decision making, and associated ecosystem modeling, important questions to ask include:

- Are multiple scenarios and multiple GCMs needed or is an ensemble mean (perhaps for each emissions scenario) sufficient?
- Do the models and emission scenarios selected match the risk framework (risk tolerant vs. risk averse)?
- Do the models chosen have good fidelity to 20th century observations at regional scales?
- If outlier models exist, can they be eliminated for objective reasons, or should their outcomes be considered equally plausible?
- Are the spatial and temporal scales of the climate information appropriate to planning or decision making?
- If downscaled information is being used, is the extra detail both necessary and realistic?
- How does the scale of that information match the ecosystem model being used?

Using Models to Reduce Uncertainty and Mitigate Its Impacts

The utility of ecological models for modelers is not necessarily the same as for ecosystem managers or decision makers. Modelers are frequently most interested in complex ecosystem dynamics, but from a management and adaptation perspective, climate-driven ecological models help to reduce uncertainty about the future and identify potential surprises and vulnerabilities. Assessing uncertainty proactively allows more informed use of models to make decisions with acceptable risks. Agencies often have established processes for risk assessment and management and can readily apply them to

Table 2. Sources, implications, and ways to reduce uncertainty in climate and vegetation models.

Source of uncertainty	Considerations for decisions	Ways to reduce uncertainty
Climate models		
Lack of understanding about phenomena and complex interactions	Our understanding of the climate system and complex interactions is limited.	Select models based on fidelity to regional and global climate use models that replicate regional cycles and trends. To the extent possible, this is largely mitigated through ongoing research.
Forcings/emissions scenarios	Future social/economic responses are not known; future climate may be warmer or cooler than projected from models if emissions are different than scenario.	Select high (e.g., A2 or A1FI), medium (A1B) and low (B1) scenarios; prioritize according to planning horizon (mid-century these are similar, late century different) and risk tolerance if not scenario planning; track current emissions relative to scenarios
Climatic variability	Interannual, decadal, or multi-decadal variations in climate intrinsic to climate system may cause departures from projected conditions; climatic variability is poorly modeled in most GCMs.	Plan for using historical interannual and decadal variability; use downscaling methods that incorporate observed variability and GCM changes (e.g., bias-corrected statistical downscaling); this is largely mitigated through ongoing research
Model choice	Individual models can have bias associated with choices of how to represent elements of climate models.	Use multiple models, preferably an ensemble of many models; choose subsets of models based on fidelity to regional climate; use models that replicate regional cycles and trends
Climate sensitivity to forcing	Climate sensitivity to forcing factors may be greater or less than widely assumed. GCMs vary in their treatment of this, but most have fairly similar approaches. The climate may be more or less sensitive to emissions than we know.	Use multiple models and multiple emission scenarios to bracket range of future outcomes
Vegetation models		
Lack of understanding about phenomena and complex interactions	Our understanding of ecological processes and complex interactions is limited.	Select models that incorporate processes of interest; understand assumptions used in the models and implications of those assumptions; use models well established in the peer-reviewed literature. This is largely mitigated through ongoing research.
Type of model	Consider process of interest—stand growth and yield, landscape dynamics, species distributions, etc.—should guide choice of model class	Learn about different models and tailor type of model to vegetation projection; if possible, use more than one type of model. If multiple objectives, use multiple models with different strengths and limitations.
Choice of model	Different models within a class represent ecological dynamics in different ways with different assumptions.	Understand assumptions, strengths and limitations of individual models; work with model developers when possible to understand input data and consequences of parameterizations; use more than one modeling approach (e.g., both process and empirical models and compare results)
Sensitivity to climate	Sensitivity outside the current ranges of climate variability is difficult to model, even for models that have "emergent" properties, like DGVMs. Interactions with higher CO_2 levels are likely, but poorly understood in real world settings.	Ongoing model development; understand individual model sensitivity and use multiple scenarios

Table 2. Continued.

Source of uncertainty	Considerations for decisions	Ways to reduce uncertainty
Propagation of uncertainty		
Many possible scenarios	If scenarios are perceived to be equally likely, uncertainty can be perceived as a major barrier.	Prioritize by risk tolerance, or use medium emissions, climate ensembles as input to vegetation models and combine with adaptive management
Propagation of errors to ecological impacts and assessments	Presumption is that small errors in initial conditions lead to larger errors in vegetation projections	Evaluate projected conditions by ability of joint climate-vegetation modeling to replicate observed conditions
Novel system behavior (surprises)		
Events or interactions not described in historical record and not anticipated from emergent properties in models	Surprises are virtually guaranteed because natural resources management by definition attempts to work on complex systems.	Planning for flexibility and resilience in general is the best mitigation. Agency structures that facilitate experimentation and reward adaptation in the aftermath of surprises encourage these features.

climate-change adaptation and mitigation (IPCC 2007, Rosenzweig and Solecki 2010, Yohe and Leichenko 2010).

The types of uncertainty in climate change projections can be classified by their sources, tractability, and implications for planning and decision-making (Table 2). The term uncertainty applies both quantitatively (to data and model parameters) and linguistically (how we describe and conceptualize what data mean) (Regan et al. 2002). Surprises, which occur rarely, present difficulties for managers and institutions, but they develop ways for dealing with uncertainties encountered frequently (Hilborn 1987). In between are uncertainties that occur infrequently, but to which we adapt and from which we learn (Hilborn 1987, Reilly and Schimmelpfennig 2000). In the latter situation, the ability to respond rapidly is most important, so broadly based monitoring systems to detect surprises as they occur are the best strategy, and when surprises do occur, having resources in reserve to cope is important (Hilborn 1987). Uncertainty in modeling and projection is mostly unsurprising in that ranges and plausible outcomes are well described, but one cannot rule out surprises entirely because of model sensitivity to the interactions of many parameters, so the strategies Hilborn (1987) describes are useful in adaptive management. Projections of climate decades or centuries into the future will never be certain—complex systems evolve in ways that are not amenable to precise forecasts—but groups of models applied appropriately allow projections with sufficient confidence to be incorporated into adaptive management.

Thoughtful choices of modeling approaches, future scenarios, appropriate scales, and levels of acceptable risk, coupled with careful testing of model output against observations, can mitigate this intrinsic uncertainty (Table 2). Using multiple models, coupled with monitoring programs to detect surprises, provides a long-term hedge against the propagation of uncertainty, cumulative effects of model bias, and omission of key processes or interactions that are necessary and sufficient to capture the important dynamics. Vegetation models differ from climate models in that the former are more heterogeneous in their scales of focus and emphasis on levels of organization (e.g., species vs. biomes). For example, projection of future vegetation in a watershed will be different if vegetation is resolved to species (e.g., gap models) or only to biomes (e.g., DGVMs). Use of these different models in combination, provides information at two taxonomic levels about how climate might affect vegetation change, and the difference between projections and their sources are themselves useful tools with which to assess uncertainty.

Some common sources of uncertainty can be particularly difficult to resolve. Both climate models and ecological models may omit key processes (perhaps because the model was constructed for a different purpose) or include processes to which the model is artificially sensitive or less sensitive than it should be. In the most difficult case, some portion of the uncertainty is irreducible because it stems from the general nature of complex systems (Roe and Baker 2007) instead of our lack of understanding of key processes. The best strategy for dealing with these commission or omission errors is awareness of limitations of what the model can achieve. Most models worth using for decision-making draw on peer-reviewed literature, but some issues are still unresolved within that literature. For example, CO_2 fertilization may offset the water limitation on vegetation distribution in a warming climate through increased water-use efficiency. Models that assume this impact is large make very different projections than those that assume it is small (Cramer et al. 2001, Bachelet et al. 2008, Lenihan et al. 2008). Scientific opinion on this issue is far from settled; until it is, these contrasting projections are difficult to incorporate in management. Multiple models and modeling approaches allow exploration of the consequences of this uncertainty, but cannot really reduce it. This uncertainty can be particularly evident at biome transitions (Bachelet et al. 2008, Lenihan et al. 2008), and could significantly affect broad-scale management. At finer scales, such as a forest project within a small watershed with an expected lifetime into the 2040s, biome-scale projections will matter less than the effects of climate change on individual species, but analogous unresolved issues in the literature may still apply. For example, while statistical models can be used to infer what may happen to individual species, the models assume that certain processes, such as biotic interactions or disturbance, are either unimportant or will remain the same with climate change. However, species are expected to respond individualistically (Davis 1986), which is likely to result in novel biotic interactions, and species whose ranges are at least partially determined by biotic interactions (the majority of species) are likely to respond in complex ways to novel environments (Elith et al. 2010). Another type of uncertainty that is difficult to mitigate is the potential for surprises that stem from a lack of understanding about important drivers, responses, interactions, or feedbacks (Hilborn 1987, Regan et al. 2002). An example of this is floods or fires for which no observed or known events are comparable in magnitude. Arguably, such surprises would be possible in an equilibrium climate, but it is possible that the extremes of today may be the common events of a future with greater extremes (Mantua et al. 2010, Duliere et al. 2011). However, if outcomes projected by models fail to occur and a surprise outcome manifests instead, there is at least an opportunity for both institutional and scientific learning.

One test of process models (including climate models and many vegetation models) is their capability to reproduce observed patterns and dynamics, but the best test may be to reproduce experimental responses under the novel conditions the model is charged with projecting. For example, can a biogeochemical model project the water, nitrogen, and carbon dynamics in a simulated, CO_2 enriched atmosphere? Of course, experiments at large scales are not always possible, but the mechanisms at the root of novel future interactions can often be tested. Statistical models should also be true to observations, but should be tested for robustness via resampling techniques to ensure that they are not excessively tuned to the observations. Consistency with other models is another litmus test. Broad agreement among ecological models with different underlying principles and different conceptual approaches when climate inputs are similar, or across multiple climate models and multiple ecological models, suggests scientific agreement (if not consensus) on sensitivity of the ecosystem response to climate. Frequent disagreement among ecological models when climate is similar suggests different assumptions and sensitivities of ecosystem response to climate among models. Frequent disagreement in output from a single ecological model with variable climate inputs suggests high sensitivity of vegetation to climate model input.

Example: reducing uncertainty in practice informed by risk tolerance

Fig. 2 illustrates a 3-step process comparing scenarios and outcomes with different risk tolerance, and represents a hypothetical example where deliberate methodology has been chosen to mitigate uncertainty. First, 18 GCMs (e.g., 18 different GCMs for emissions scenario A1B from the PCMDI archive, Meehl et al. 2007) are evaluated for their regional bias in temperature, precipitation, and seasonal cycle during the 20th

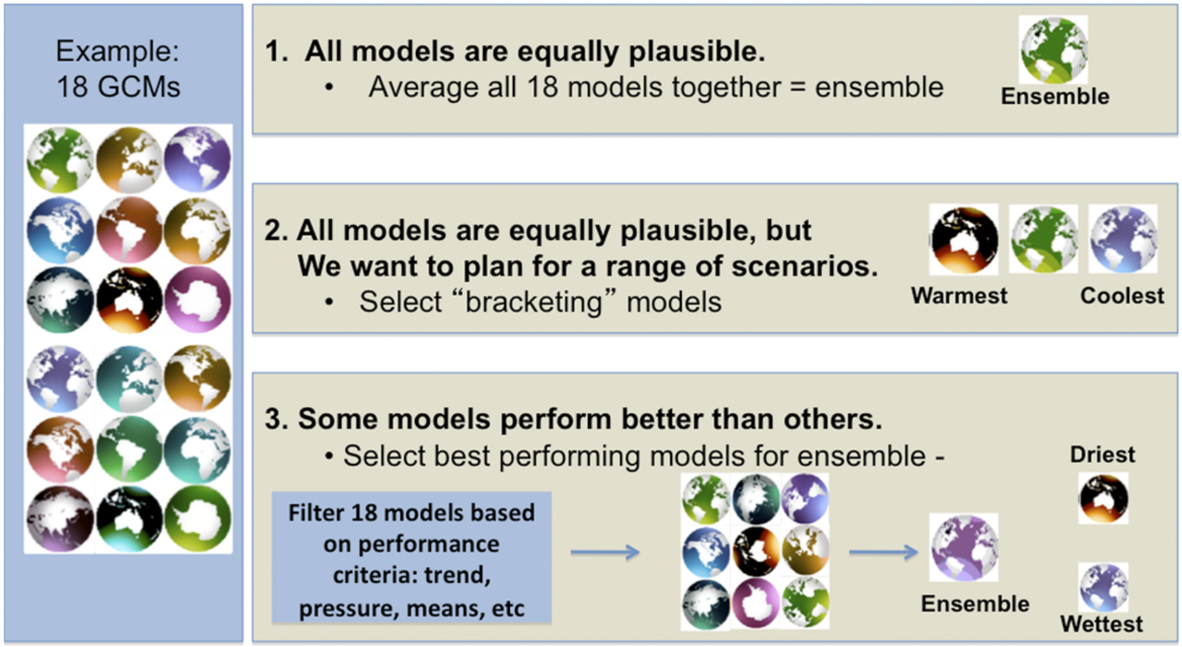

Fig. 2. One approach to limiting uncertainty about future climate is choosing relevant subsets of global climate models (1), using ensemble means and (2) bracketing scenarios for downscaling (e.g., "delta" method) (3), and combining these approaches for a filtered subset of models. Planet image modified from original online at ⟨www.psdgraphics.com⟩.

century (Fig. 2, panel 3). Assuming that a prerequisite for future performance is current performance, this can decrease uncertainty about model sensitivity and the performance of GCMs—poorly performing models are eliminated. The 10 models with best fidelity to the 20th century record are selected, their regionally specific estimates of change in temperature and precipitation ("deltas") are averaged, and a gridded observed climatology is perturbed by those deltas to obtain future downscaled estimates.

We assume that the average of multiple models reduces uncertainty associated with individual model parameterization and we downscale the projections to a useful resolution for sub-regional applications. In this example (Fig. 2, panel 2), the model with the warmest bias and the model with the coldest bias for the season and process of interest are used to perturb the field in the same way to provide bracketing scenarios. This addresses the uncertainty that the future may be warmer or cooler than the mean of the best models. The three future climate scenarios (coolest, ensemble mean, and warmest) are then used as input into an ecosystem model. A more robust approach would use multiple ecosystem models. This yields three estimates of future process variation and controls for uncertainty associated with vegetation model sensitivity to climate. The ensemble mean is robust, coming from models with good fidelity to observed climate, and planning around this scenario could be considered risk neutral. The warmer scenario is risk averse—planning for it would need to assume larger potential changes in vegetation (perhaps respiration) because the rate of warming is faster. The cooler scenario is risk tolerant—planning for this scenario assumes that the possibility of warmer conditions warrants fewer changes in management. This third step connects uncertainty to risk in that a gradient of risk can be essentially overlain on the range of uncertainty.

In the long term, it is key to understand *why* models are at odds with each other and why some models are such outliers. If one or more of the main processes affecting climate currently becomes less important and a currently secondary becomes more important, these outlier models could be superior, though we would have no way to know this before hand. In this case, eliminated models could well be the closest to the "true" model. This is resolvable both through continued model development via research and through monitoring and experimentation, but such evolution may or may not improve decisions, and waiting for better information to make decisions may ensure a narrower range of choices. In the next section, we turn our attention to model output in the context of decision making and risk.

Using Model Output to Make Decisions with Known Risks

Using projections from climate and ecosystem models in decision making can extend models beyond what they were intended to do –to better understand a system through iterative refinement of concepts and synthesis of scientific knowledge. Using them in decision-making brings up questions such as "What assumptions and choices in the modeling could undermine these projections significantly?" and "What future events could happen that would change the confidence in these projections, and how likely are those events?" We propose the following questions that can be asked of all models to identify common pitfalls, highlight common misuses, and address uncertainty that stems from their misapplication. The answers will determine whether a model can capture the ecosystem response of interest or whether model limitations undermine its ability to project changes well enough for decision making.

- *How well does the model simulate observed conditions?* This is the ultimate litmus test for models—discrepancies between observed dynamics and model simulations usually represent excluded or poorly parameterized processes (e.g., land use), incorrect assumptions, or scale / domain problems that must be reconciled.
- *Are there major unresolved scientific issues associated with the model's implementation?* It is sometimes necessary to include partially understood or incompletely verified relationships or processes in both vegetation and climate models. If these represent best approximations, their inclusion is not necessarily problematic. Models may be very sensitive to precisely these relationships, however, so they may add substantially to model uncertainty.
- *Was the model intended to make the projections it is being asked to make and is it capable of doing what it is being asked to do?* Models are frequently pressed into service to generate projections outside their purview. Sometimes such extension merely represents the evolution of an already good model, but it may also result in output that receives more weight than it should simply because it is model generated. It is key to understand what the model was constructed for and how far outside its boundaries it is being applied.
- *Are the native spatial, temporal, and biological scales of the model output appropriate for the scale of decision making? Does it matter (and what are the consequences) if they are not?* For spatially explicit models, and often for spatially implicit models, there is a scale (pixel or grain size) associated with the model projections or processes. It is key to understand this scale and ensure that cross-scale inferences are not constructed inappropriately. For example, assuming that a hemispheric climate trend must be represented in every part of the hemisphere is erroneous, just as extrapolation from a single observation to a global phenomenon is erroneous. Temporal scale has analogous issues associated with it.
- *Are the necessary processes, responses, and interactions required to describe ecosystem response incorporated in the model?* What are the consequences if they are not? What important processes are not considered in the model? For example, is a vegetation model static or dynamic with respect to disturbance that alters vegetation, which in turn affects disturbance? Does static vegetation change model output on relevant time scales? It is possible, for example, that the dynamic vegetation influence on basin-scale hydrology decreases as scale increases. A hydrologic model that needs to estimate streamflow or

runoff in a small basin over the course of a century will be crippled by static vegetation assumptions because the real vegetation could change substantially, but a much larger basin might or might not be as affected by the same problem because many small changes could average out or they might be a larger scale change analogous to complete restructuring in a small basin.

- *Do multiple models addressing the same question and starting with similar assumptions produce similar results?* Is there sufficient agreement among modeling approaches that the sensitivity of model parameters and architecture is not too great? If divergence among model results is evident, is it in specific details or general features? The former might indicate minor process uncertainty or slight differences in parameters (or possibly models that are not entirely independent), whereas the latter might indicate large differences in the sensitivity or scientific basis of the models in question. Model development and model lineages are sometimes shared, so it may be important to not that if there is agreement, the models need to be independent for the approaches to risk and uncertainty described above to hold.

Conclusion

The role of model output in decision-making by managers is to bridge the gap between understood reality and potential changes to that reality in the future. Climate change and its impacts on vegetation and natural resources point to a future that is quite different from even the recent past. In any future, particularly those describing a world affected by climate change, surprises are going to be difficult to navigate in management. So models become a good way—some would argue the best way—to anticipate the future and to develop strategies based on our own mandates, objectives, and vision. Models incorporate imperfect information and are a simplified version of reality, but by understanding these imperfections, we can use models be used to decrease the uncertainty associated with the future. This narrowing of future uncertainty based on projections translates into narrowing the risk profile for important resources—it effectively allows more informed decisions based on the likelihood of alternate futures. Information from multiple models should be used in decision making to provide projections about the future and to decrease uncertainty, rather than to "predict" what *will* happen. Models will not make decisions for anyone and will sometimes make decisions more difficult because of the tradeoffs they reveal. By incorporating model-based information into existing risk assessment strategies and incorporating local knowledge, particularly at the scales of project planning where global and regional climate or general ecological projections become less certain, the basis for decision and action can be strengthened.

Reducing uncertainty in climate and ecosystem model projections is only one part of decision making under uncertainty. When confronted with multiple future scenarios that are all plausible, if not equally likely, the real question is "How does this information change decision making?" The answer to that question involves prioritization of objectives, vulnerabilities, risk tolerances, monitoring, assessment, and correcting the course of management to achieve objectives. Climate and ecosystem models are a basis of decision making, when coupled with adaptive management they reduce future uncertainty and provide a hedge against its consequences. Models may appear to complicate the analytical approach to decision making, but in the end they reduce the uncertainty associated with those decisions.

This is not to say that models should be the basis for all decision-making, nor that all models should be used in decision making. Models are important *tools,* and both models and decisions, even if made with the best available science, must be reassessed when they don't work, as should the underlying science. There are potential conflicts between decisions implied by model projections and the regulatory environment in which the actions that result from those decisions must take place (Littell et al. 2011*a*), making the case for an improved science management partnership (Joyce 2003). Decision makers and managers necessarily have different needs from models—and sometimes from science—than model builders and scientists. Recent approaches to "climate services" (Miles et al. 2006) suggest that this partnership is an iterative relationship where science informs management but management needs define the progression of science. For example, managers are quite capable of pointing out un-incorporated variables or suggesting model refinements that would make output more useful to them. Science–management partnerships can also design and implement monitoring systems that can be used to improve and validate model quality, leading to better models with less uncertainty.

Perhaps the most important message we offer is that scientific uncertainties about changes in climate or the projections of impacts on resources do not present fundamental barriers to management and adaptation to climate change. Instead, uncertainty can be purposefully mitigated with appropriate attention to model limitations and ongoing re-assessment based on monitoring. The institutional barriers to adaptive capacity (e.g., Moser and Luers 2008), such as static approaches to systems that are inherently dynamic, may ultimately be more limiting than scientific uncertainty (Chapin et al. 2006).

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