Future climate vulnerability – evaluating multiple lines of evidence

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Climate change will markedly alter the structure and function of ecosystems, with important implications for land management. Yet scientists' ability to predict future ecological conditions is hampered by uncertainty in both climate projections and ecological responses to climate change. More data are now available – from small-scale experimental results to continental vegetation model projections – to improve understanding of climate vulnerability. Integrating these resources can strengthen vulnerability assessments but managers may become skeptical of the assessment process when information sources generate conflicting outcomes. We discuss practical approaches to integrating multiple lines of evidence in vulnerability assessments, and illustrate these approaches using three case studies: Oregon white oak in the Willamette Valley, whitebark pine in south-central Idaho, and sagebrush steppe on the Columbia Plateau. These cases demonstrate that although weaving together multiple lines of evidence can be challenging, unique insights can emerge even when there is divergence in projected changes.

Front Ecol Environ 2017; 15(7): 367–376, doi:10.1002/fee.1516

Changes to the climate since the Industrial Revolution have already altered the distribution and abundance of plant and animal species (Walther *et al.* 2002; Parmesan and Yohe 2003; Root *et al.* 2003; Chen *et al.* 2011). As species respond to climate change, the structures and functions of ecosystems are also likely to undergo substantial changes but it is hard to predict what these will be (Staudt *et al.* 2013). To successfully manage ecological systems in the face of these changes, land managers need to understand how vulnerable a species or system is likely to be to climate alterations. Climate-change vulnerability can be defined as the degree to which a species or system is likely to be negatively affected by climate change (Pacifici *et al.* 2015). For example, species or systems that are sensitive to changes in snow cover – such as wolverines (*Gulo gulo*), which rely on spring snow for denning (McKelvey *et al.* 2011), or high-elevation trees, which are limited by snow cover and minimum temperatures (Halofsky and Peterson 2015) – are considered particularly vulnerable to climate change. Vulnerability assessments play a key role in the development of sound adaptation strategies, including planning and management approaches used to reduce the impacts of climate change (Glick *et al.* 2011).

In a nutshell:

- Integrating multiple lines of evidence is challenging but is a critical best practice when conducting climate vulnerability assessments
- Finding agreement across projected future impacts and ecological conditions can increase confidence in projections
- Careful consideration of the scale, assumptions, and limitations associated with each source of information can help resolve apparent disagreement, expose uncertainty, and highlight potential system sensitivities
- Reviewing diverse types of information can help managers visualize a wide range of plausible future ecological scenarios, leading to more robust and flexible vulnerability assessments and adaptation strategies

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Access to vulnerability data, particularly output from quantitative models, has historically been limited (Klausmeyer *et al.* 2011). Thus, despite the theoretical importance of using multiple sources of evidence, the majority of case studies involving adaptation planning have relied on expert opinion to evaluate climate vulnerability (Glick *et al.* 2011; Poiani *et al.* 2011; Cross *et al.* 2012). However, an increasing number of predictive modeling approaches now exist for implementation at regional to continental scales (eg Bachelet *et al.* 2001; Lawler *et al.* 2009; McKenney *et al.* 2011). Integrating these resources is important because although each approach has inherent limitations, each yields a unique understanding of different aspects of climate vulnerability (Dawson *et al.* 2011; Rowland *et al.* 2011). Natural history and experimental data can, for instance, identify potential physiological responses of individual organisms to climate change, whereas mechanistic vegetation models project vegetation change based on the aggregated effects of multiple ecological processes in addition to climate change. However, there is a risk that managers will dismiss whole classes of data due to inherent limitations, discard models that disagree, or conclude that projected changes are too uncertain to be useful in planning and management. Yet prematurely disregarding data and models increases the chance that vulnerability assessments – and subsequent adaptation plans – will fail to account for potentially severe climate-change impacts (Millar *et al.* 2007).

There is a clear consensus that consulting multiple sources of information is a valuable approach (Dawson *et al.* 2011; Rowland *et al.* 2011; Halofsky and Peterson 2016). In practice, however, integrating multiple information sources to identify key vulnerabilities is challenging because of differing methodologies and (often) disagreement about potential future effects. To use a wide range of resources effectively, practitioners need concrete examples of how to meaningfully integrate existing resources into vulnerability assessments. We discuss how to integrate and interpret multiple lines of evidence, present the results from case studies that evaluate climate vulnerability using an array of existing datasets, and illustrate how diverse and sometimes conflicting lines of evidence can be interpreted to develop a coherent picture of potential future climate vulnerability.

Integrating multiple lines of evidence

An ever-expanding suite of metrics, models, approaches, and datasets is available to inform climate change vulnerability assessments. Integrating existing datasets is difficult because each one is created with different assumptions, spatial or temporal scales, and methodologies. Despite being messy and challenging to work with, this independence and diversity is a strength (Morin and Thuiller 2009). For example, when multiple independent models project similar climatic changes, researchers generally have more confidence in those projections (Hansen *et al.* 2001; Littell *et al.* 2011). Similarly, comparing ecological response projections based on a variety of modeling approaches (Morin and Thuiller 2009) or climate projections (Rehfeldt *et al.* 2012) can give greater confidence in future outcomes if those projections agree (Pearson and Dawson 2003). When model results also align with scientists' understanding of the ecology and natural history of a species or place, it is easier to explain the projected changes.

Although agreement among different lines of evidence can build confidence in a particular future outcome, in many cases such agreement will be elusive. For instance, as climate models have proliferated and become more complex over time, agreement among climate projections has not necessarily increased (Maslin and Austin 2012; Rupp *et al.* 2013). While disagreement among projections can be initially frustrating, understanding sources of such disparity potentially contributes important information. When using quantitative ecological response models, scientists may generate results that vary depending on climate projections, downscaling approaches (ie the process of translating global climate projections to a local scale), modeling approaches, and specific model formulations (Lawler *et al.* 2006; Elith and Graham 2009; Morin and Thuiller 2009).

Comparing results from a single model but using different climate projections within that model highlights uncertainty due to differences in climate-change projections. By contrast, comparing results from different models using the same climate data can yield insight into the influence of model assumptions on projected changes. For example, climatic niche models provide information about climatic suitability alone for the modeled species, whereas mechanistic models incorporate many additional dynamics including dispersal, competition, fire, and CO_2 fertilization. Disagreement between results of different models can reveal areas for further research (Pearson and Dawson 2003) or help identify impacts that arise due to climate changes alone (climatic niche models) versus how climate impacts may be moderated, or enhanced, by interactions among a more complex set of drivers (mechanistic models). Finally, exploring inconsistencies between model projections and known natural history characteristics of the target may identify missing drivers or interactions, particularly processes that operate at spatial or temporal scales too fine to be captured by broad-scale models (Willis *et al.* 2015).

Case studies

We present three case studies illustrating practical examples of how multiple lines of evidence can be integrated to create a coherent picture of potential climate vulnerability (Figure 1). These case studies result from adaptation workshops we hosted in 2012 with landscape managers in the US Pacific Northwest. Each of the case studies targets a conservation priority identified by regional managers, and together the three cases represent a geographically and ecologically diverse set of natural resources. The case studies also vary in the extent to which the available evidence converges on a similar prognosis for vulnerability, which can be thought of as a function of *sensitivity* (how strongly a species or system will respond to climate changes), *exposure* (the amount of climate change the species or system may experience), and *adaptive capacity* (the ability of the species or system to adapt to climate impacts) (Smit and Wandel 2006).

Much has been written on the strengths and limitations of different information resources for assessing vulnerability (Hampe 2004; Kearney and Porter 2009; Willis *et al.* 2015). Here, we briefly discuss the potential applicability and limitations of the data sources used in our case studies (Table 1). We relied on a climate change sensitivity database (Case *et al.* 2015) and the general literature to identify each target's potential physiological and ecological sensitivities to climate change. We used downscaled climate projections to evaluate projected changes in particular climate variables (Shafer and Bartlein 2015) relevant to the climate sensitivities of the selected conservation priority within each region. We compared this trait-based assessment with projected changes in the area and the distribution of the climatic niche (ie the current set of climatic conditions found within the target species' range) for each species (Case and Lawler, unpublished). We further evaluated relative climate exposure by calculating the mean and maximum climatic velocity – that is, the rate at which the climatic conditions at any given location are projected to move across the Earth's surface (Hamann *et al.* 2015) – for each case study region. Finally, we evaluated potential impacts to the species' habitat by reviewing projected changes in vegetation types using both a climatic niche model (Rehfeldt *et al.* 2012) and two mechanistic models (Bachelet *et al.* 2001; Shafer *et al.* 2015). For each vegetation type, the climatic niche model projects the extent to which, and where, the climatic conditions currently associated with that vegetation type shift in the future. The mechanistic models project vegetation changes that result from interactions between multiple ecological processes such as climate change, fire, and CO_2 fertilization. In all cases, we used model projections to gain a descriptive sense of the direction, type, and intensity of potential changes to habitat suitability within the study region rather than to classify particular sites as more or less vulnerable.

Figure 1. *Three case study landscapes and conservation targets with varying degrees of climate vulnerability: (a) the sagebrush steppe system of the Columbia Plateau has been largely converted to agricultural uses and faces future threats from changes in water availability and altered fire frequencies; (b) climate may influence conifer competition, fire, and drought dynamics for Oregon white oak woodlands in the Willamette Valley; (c) reduced snowpack and warmer temperatures could affect whitebark pine's competitive ability and the prevalence of forest pests and pathogens within the Pioneer Mountains–Craters of the Moon Region of Idaho.*

Oregon white oak in the Willamette Valley, Oregon

Within the Willamette Valley of Oregon (hereafter "Valley"), Oregon white oak (*Quercus garryana*) is usually found in open canopy savanna and prairie ecosystems and serves as a critical food and habitat resources for associated wildlife. This species of oak is drought tolerant and typically has a competitive advantage over conifers in warmer and drier growing seasons (Stein 1990). There is strong agreement among climate projections that summers are expected to be hotter and likely drier in the Valley (Shafer and Bartlein 2015), which may benefit *Q garryana*. There is also strong agreement among climatic niche model projections that climate conditions will remain suitable or become even more favorable for this species (Figure 2a). Projected mean climatic velocity is very low within the Valley, indicating generally low climate-change exposure (Table 2).

There was substantial variation in the type of forest projected to develop in the Valley, depending on the vegetation model and climate projections used (Figures 3–5; Table 2). Each vegetation model was run using several different climate projections. For two of the three vegetation models, namely the Lund-Potsdam-Jena (LPJ) model and climatic niche model, projected vegetation types were similar for the Valley regardless of the climate projection used, indicating that, for these models, the differences in climate projections had little impact on projected future vegetation type. By contrast, the MAPSS-CENTURY 1 (MC1) model projected markedly different forest vegetation types, depending on which climate projection was used. According to this model, future vegetation is sensitive to variation in climate projections.

Comparing projected vegetation from different models that used the same climate projection can identify the extent to which the vegetation models agree on potential

Table 1. Descriptions of the climate vulnerability resources used in the case studies

	Applications	*Limitations*	*Spatial scale*
Trait-based sensitivities: Identify species' traits that potentially amplify climate sensitivity.	Identify potential vulnerabilities potentially missing from formal models. Independent of climate projections.	Limited knowledge of species' or system's climatic requirements. Difficult to assess net impact from conflicting sensitivities.	Fine-scaled, organismal level.
Downscaled climate projections: Projected changes to direct and derived climate variables.	Provide insight into exposure to climate change; can be linked to known or expected sensitivities to evaluate trait-based vulnerability.	Uncertainty in emissions levels and climate response to emissions leads to variation in climate projections.	Accuracy decreases as temporal and spatial resolution increases.
Climatic velocity: The rate at which species must move to remain within similar climatic conditions.	Larger velocities indicate higher climate-change exposure and risk.	Results vary depending on spatial scale, climate variables, and threshold definition of "similar" climatic conditions.	Dependent on available climate grid resolution (see above).
Climatic niche projections: Statistically model present and future climatic suitability.	Identify whether climatic suitability is likely to remain stable, improve, or decline for a target. Relatively fast to implement with minimal data requirements, available for many species.	Generally do not include factors such as competition, dispersal, and evolutionary capacity, which also determine range boundaries.	Most applicable at broad (ie continental) scales, where the effects of fine-scaled topography and biological interactions play a smaller role.
Mechanistic vegetation models: Project vegetation changes using biogeochemistry, biogeography, disturbance, and climate.	Incorporate more factors than statistical models. Based on mechanistic relationships rather than statistical correlations.	Complex and time consuming to run. Parameters are often based on limited empirical data. Difficult to interpret which factors drive the outcome.	Limited by the resolution of input data. Models broad vegetation types, rather than specific species or systems.

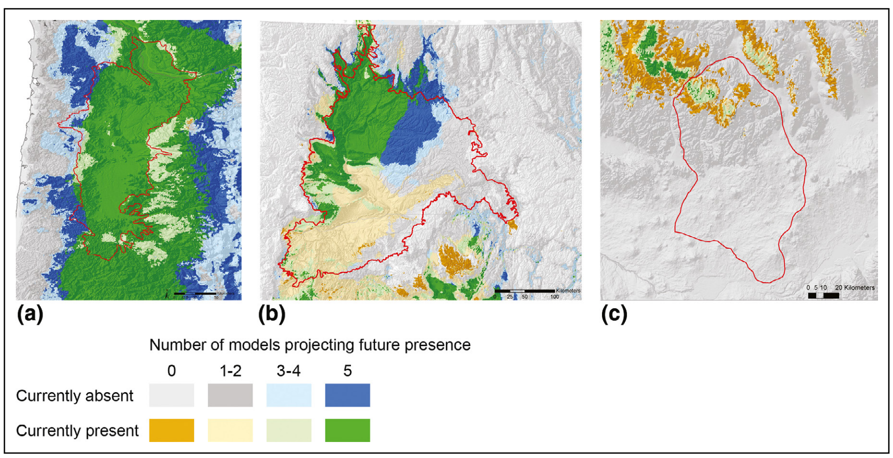

Figure 2. *Climatic niche model projections for (a) Oregon white oak (*Quercus garryana*), (b) big sagebrush (*Artemisia tridentata*), and (c) whitebark pine (*Pinus albicaulis*). Case study landscapes are outlined in red. Projections were created using the Random Forest classification tree (see Case and Lawler 2017 for modeling details), for the 2080s, using the A2 emissions scenario and five global climate model projections: Bjerknes Centre for Climate Research–Bergen Climate Model version 2 (BCCR BCM 2.0), Canadian Centre for Climate Modelling and Analysis (CCCMA), Commonwealth Scientific and Industrial Research Organization climate system model version 3.0 (CSIRO Mk3.0), Institute for Numerical Mathematics Climate Model version 3.0 (INMCM 3.0), and Model for Interdisciplinary Research on Climate (MIROC) version 3.2 (medres). Green colors indicate stable climatic suitability, orange indicates areas of lost climatic suitability, and blue/dark gray indicate newly climatically suitable areas. Darker colors indicate stronger model agreement. Data provided by Case and Lawler (unpublished).*

future vegetation. This comparison is challenging to carry out in practice because each model classified forest types differently. Only one climate projection, based on the A2 emissions scenario and a General Circulation Model (GCM) known as the UK Meteorological Office–Hadley Centre Atmospheric Model version 3 (UKMO-HadCM3) (Pope *et al.* 2000), was used in all three vegetation models. Under this climate projection, both the climatic niche model (Figure 4) and the mechanistic MC1 model (Figure 5) project an expansion of conifer forest from the east, whereas the mechanistic LPJ model projects minimal change to historical vegetation (Figure 3). The contrast between the MC1 and LPJ projections indicates that vegetation projections can differ even when using the same type of model (ie mechanistic) and similar climate data (same GCM, emissions scenario, and time period), emphasizing the uncertainty associated with current understanding of how these vegeta-

Table 2. Summary and comparison of results from the case study vulnerability assessment for each conservation target

	Data sources	*Oak*	*Pine*	*Sagebrush*
Climatic suitability	Sensitivities	Growing season precipitation	Temperature and snowmelt	Temperature and snowmelt
	Projected climate changes[1]	Hotter, drier summers	Reduced snow	Warmer winters and less snow
	Climatic velocity[2]	$\bar{x}$ = 1.1; Max = 1.6	$\bar{x}$ = 8.3; Max = 26.2	$\bar{x}$ = 5.0; Max = 17.4
	Projected change in climatic niche area[3]	Stable	Substantial (57–93%) contraction	Net expansion or contraction depending on climate projection
Vegetation suitability	Dominant projected future biome[4]	Montane conifer forest	Great Basin montane scrub	Great Basin shrub-grassland, Mojave desertscrub, and/or Great Basin montane/desert scrub
	Dominant projected biome[5]	Coastal conifer forest	Cool mixed needle- and broadleaved forest	Shrub steppe is replaced by either grassland or forest of various types
	Dominant projected biome[6]	Three alternative outcomes: (1) no change, (2) east-side conifer forest, or (3) temperate warm and subtropical mixed forest	Not available for this region	Temperate shrubland largely persists with some forest encroachment
Fire regime	Increased frequency and intensity[7]	Fire may give oaks a competitive advantage, but frequent intense fires may be harmful	Infrequent fires are beneficial; frequent fires are harmful	Frequent, mild burns are beneficial; large intense fires increase risk of *B tectorum* invasion
Interspecific interactions	Literature review	No significant species interactions documented	White pine blister rust and mountain pine beetles	Invasive cheatgrass (*B tectorum*)

Notes: [1]Shafer and Bartlein (2015); [2]Hamann *et al.* (2015); [3]Case and Lawler (unpublished); [4]Rehfeldt *et al.* (2012); [5]Shafer *et al.* (2015); [6]Rogers *et al.* (2011); [7]Rogers *et al.* (2011), Littell *et al.* (2010), Westerling *et al.* (2006).

tion types may respond to climate change. More explicit research comparing existing mechanistic vegetation models is needed to better understand when and why these models may disagree.

Despite the variation in projected vegetation types, all three vegetation models project that, in the absence of human management, the Valley will remain forested, with a trend toward conifer forest (Figures 3–5; Table 2). An increase in conifer forest cover in the Valley would presumably have negative impacts on oak populations (eg Devine and Harrington 2006). However, the vegetation models reviewed here are not designed to identify local variation within forest types. For instance, there are large oak populations in the south Puget Sound region and on the east side of the Cascades,

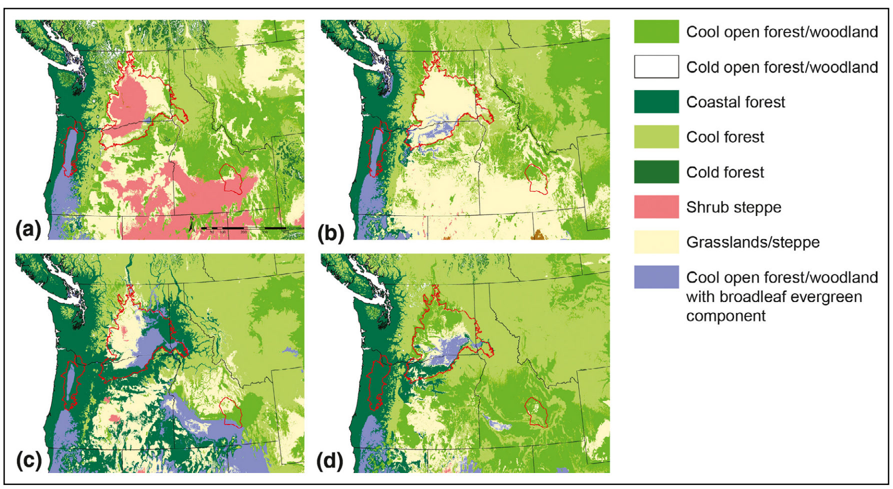

Figure 3. *Modeled current (a) and future (b–d) vegetation types. Vegetation types were modeled using the Lund-Potsdam-Jena dynamic general vegetation model (Shafer* et al. *2015). Projected future vegetation is for the 2080s, using the A2 emissions scenario. Future vegetation was projected using three General Circulation Models: (b) Community Climate System Model version 3 (CCSM3), (c) UKMO-HadCM3, and (d) Coupled Global Climate Model version 3.1 T47 spatial resolution [CGCM3.1(T47)]. For projections based on the A1B emissions scenario and two other GCMs, see WebFigure 1.*

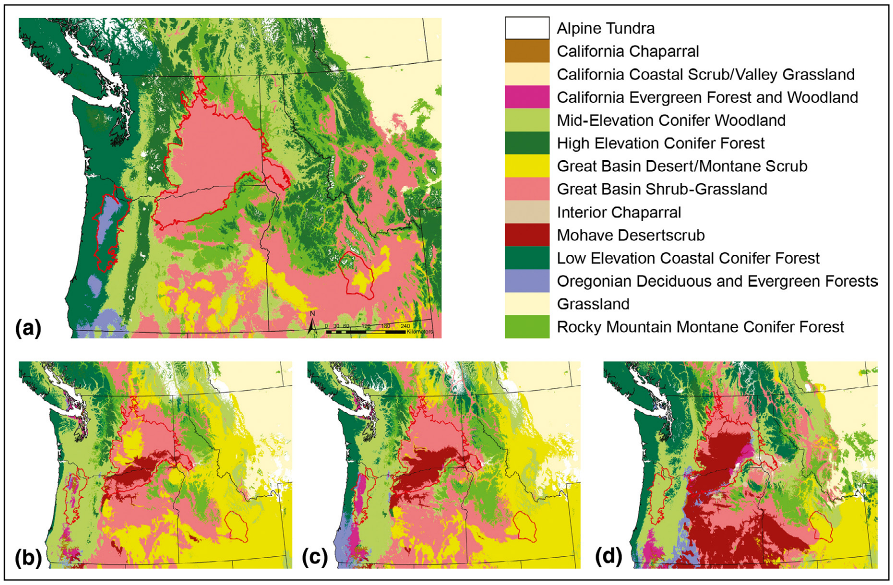

Figure 4. *Predicted current (a) and future (b–d) vegetation types. Vegetation types were modeled using the Random Forest classification tree, a type of climatic niche model (Rehfeldt* et al. *2012). Projected future vegetation is for the 2080s, using the A2 emissions scenario. Future vegetation was projected using three General Circulation Models: (b) UKMO-HadCM3, (c) Geophysical Fluid Dynamics Laboratory Climate Model version 2.1 (GFDL CM2.1), and (d) CGCM3.1(T63).*

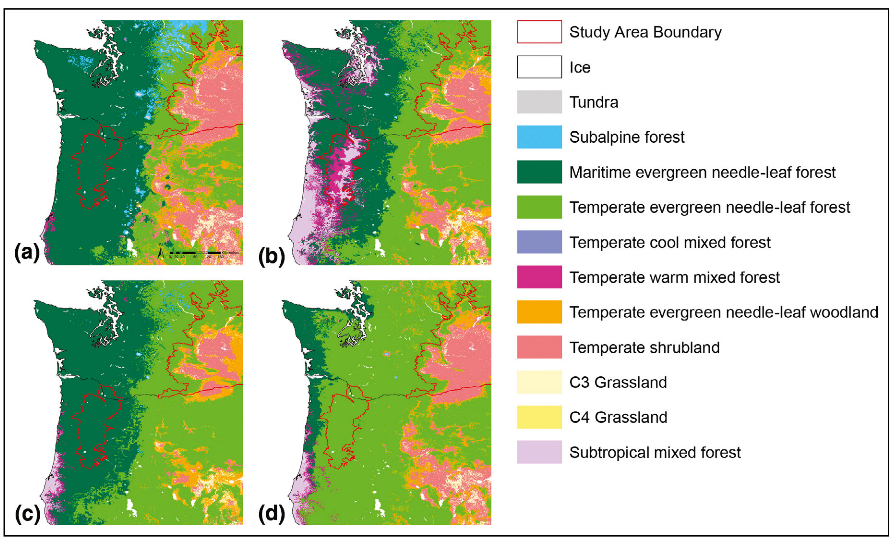

Figure 5. *Modeled current (a) and future (b–d) vegetation types. Vegetation types were modeled using the MC1 dynamic general vegetation model (Rogers* et al. *2011). Projected future vegetation is for the 2080s and the A2 emissions scenario. Future vegetation was projected using three General Circulation Models: (b) MIROC 3.2 (medres), (c) CSIRO Mk3.0, and (d) UKMO-HadCM3. Data provided by (Rogers 2009) via Databasin.org.*

but even the current vegetation in these regions is classified as maritime or mid-elevation conifer forest by these vegetation models. Oregon white oak's current distribution overlaps that of the forest types projected to move into the Valley, indicating that oak persistence may be possible despite potentially dramatic projected vegetation changes.

Oregon white oak is considered sensitive to climate change because of its association with fire-sensitive grasslands and pressures from forest encroachment (Case 2010). Low-intensity burns can benefit oaks by reducing conifer competition, but high-intensity burns can cause mortality (Agee 1996). The MC1 model projects an increase in burn severity and extent in western Oregon under all climate projections (Rogers *et al.* 2011), which would likely reduce suitability for oak. Despite increased drought and fire frequency, which could theoretically favor grassland, both mechanistic vegetation models project the future presence of forest in this landscape. This result is most likely driven by CO_2 fertilization, which increases the water use efficiency of trees, favoring conifers (Bachelet *et al.* 2001). Finally, other forest and fire management actions, such as prescribed burns and conifer removal, are important drivers in this system but are not included in the vegetation models.

In this case, multiple lines of evidence converge on a message of cautious optimism for Oregon white oak in the Valley. There is strong agreement that the region will remain climatically suitable for this species and most likely forested. Whereas forest type is moderately uncertain, none of the projected forest types necessarily preclude oak presence. Despite these reasons for optimism, considerable uncertainty remains regarding the fine-scaled impacts of fire, the effects of CO_2 fertilization, conifer encroachment, and human management on this system. In addition, while Oregon white oak may persist, climate change could have more substantial impacts on the oak savanna ecotype than on the species itself.

Whitebark pine in the Pioneer Mountains–Craters of the Moon region, Idaho

Whitebark pine (*Pinus albicaulis*) has a broad geographical distribution but a preference for mid- to high-elevations. Summer snowmelt is a critical water source for growth and seedling survival, and snowpack controls encroachment of lower elevation species (Burns and Honkala 1990). Climate projections forecast warmer temperatures and reduced snowpack in the region, which would lead to a decline in climatic suitability. Climatic niche model projections support this finding, given that climatically suitable areas are projected to contract under all scenarios (Figure 2c). This study region had the highest mean climatic velocity of the three case study regions, indicating high climatic exposure.

Vegetation projections for the Pioneer Mountains–Craters of the Moon (hereafter, "Pioneer–Craters") region differed between the climatic niche and mechanistic LPJ models (MC1 model projections were not available for the Pioneer–Craters region). Climatic suitability for Rocky Mountain montane and subalpine forest – the vegetation type currently associated with whitebark pine – declines under climate niche model projections, and the climate instead becomes more similar to that found in Great Basin montane scrub systems (Figure 4). According to the mechanistic LPJ model, cool open forest woodland is projected to expand upslope, replacing high-elevation cold forest under the majority of climate projections (Figure 3).

Whitebark pine is adapted to relatively long fire-return intervals (time between consecutive fires in a given area; eg 50 to 500 years) (Tomback *et al.* 2001). Recent warming and earlier spring snowmelt have led to more frequent large wildfires and longer wildfire seasons (Westerling *et al.* 2006), which are projected to continue in the future (Westerling *et al.* 2006; Littell *et al.* 2010). Whitebark pine is susceptible to outbreaks of mountain pine beetle (*Dendroctonus ponderosae*) and the non-native fungus, white pine blister rust (*Cronartium ribicola*). Warmer temperatures and reduced snowpack may lengthen the growing season for both blister rust and pine beetles, exacerbating these impacts in some areas (Larson 2011). In addition, trees stressed by heat and drought are more susceptible to pest infection and damage (Millar *et al.* 2012).

Most evidence points to a decline in the extent of whitebark pine in the Pioneer–Craters region as a result of climate change. Reliance on high-elevation habitat and snowmelt makes whitebark pine sensitive to increasing temperatures. Niche models project reductions in climatic suitability by the end of the century. Finally, climate change could potentially alter the fire regime and exacerbate existing stresses from insects and pathogens.

Sagebrush steppe on the Columbia Plateau, Washington State

This case study focused on the sagebrush steppe vegetation type. Models to evaluate vulnerability were available for two ecological systems – intermountain basin big sagebrush steppe (hereafter, "sagebrush steppe") and intermountain basin big sagebrush shrubland (hereafter, "sagebrush shrubland") (NatureServe 2015) – as well as for the species known as big sagebrush (*Artemisia tridentata*).

Several experimental studies have investigated the impacts of temperature and precipitation on *A tridentata*, a moderately generalist species with several subspecies adapted to local climatic conditions (Kolb and Sperry 1999). In particular, *A tridentata* tolerates a wide range of temperatures, making it unlikely that increased temperatures will have a major impact on germination or seedling establishment except at extreme range margins (Schlaepfer *et al.* 2015). By contrast, moisture availability is a crucial determinant of seeding survival (as reviewed in Schlaepfer *et al.* [2014]). Projected increases in winter precipitation for the Columbia Plateau (hereafter, "Plateau") have the potential to increase growth of *A tridentata* on deep soils but may decrease growth on shallow soils, indicating that climate-change impacts may vary spatially (Germino and Reinhardt 2014).

For all three targets (sagebrush steppe, sagebrush shrubland, and *A tridentata*), climatic niche models project a mix of stability, expansion, and contraction on the Plateau (Figure 2b). In all cases, less than 50% of each target's current range is projected to remain climatically suitable. Under three climate projections, the net area of climatic suitability declines, whereas under two projections, net area expands. Projected climatic velocity for the Plateau is moderately high (Table 2).

Projections of future vegetation types on the Plateau vary widely. The climatic niche vegetation model projects that the northern half of the Plateau will remain climatically suitable for Great Basin Shrub-Grassland but that the climate in the Plateau's southern half will become more similar to that of Mojave Desertscrub (Figure 4). The mechanistic MC1 model projections, which cover the western half of the Plateau, forecast varying degrees of conifer encroachment (Figure 5). By contrast, the LPJ model projects nearly complete transition of shrub steppe on the Plateau to either grassland (under drier projections; Figure 3b) or different types of forest (under wetter projections; Figure 3, c and d).

Cheatgrass (*Bromus tectorum*) is a European species introduced to western North America that outcompetes many native plants and has invaded sagebrush steppe ecosystems across the Plateau. Climatic niche models indicate that climatic suitability for cheatgrass on the Plateau will either stay the same or decline (Bradley 2009). However, increased CO_2 concentrations may benefit cheatgrass by changing its nutrient composition and subsequently decreasing its desirability to grazers (Ziska *et al.* 2005) and increased fire frequency will likely give the species a competitive advantage over sagebrush (D'Antonio and Vitousek 1992; Balch *et al.* 2013).

The projected future of sagebrush steppe on the Plateau is complex and variable. Nevertheless, some trends can be discerned. First, climatic niche models all indicate that some areas of the Plateau, particularly in the northern half, will remain climatically suitable for sagebrush. Second, despite substantial differences between projections from mechanistic vegetation models, all of them forecast some level of forest encroachment. However, the extent and type of projected vegetation transformation varies widely, emphasizing that more detailed modeling for this region, as well as long-term monitoring to detect early changes, are potentially important next steps.

Conclusions

Evaluating multiple independent projections of climate impacts can deliver a richer picture of potential future change for conservation targets at the landscape level. However, as our case studies illustrate, the degree of convergence among multiple lines of evidence can vary. We found substantial agreement across projections of climatic suitability for whitebark pine and Oregon white oak, but far less agreement across projections for sagebrush steppe.

In all three cases, had we relied on only one or even two lines of evidence, we would have missed important potential impacts and uncertainties. For Oregon white oak, climatic changes alone may increase the oak's competitive advantage, but mechanistic models project that conifer forest will remain dominant in the region. Although oaks can persist in conifer-dominated landscapes, mechanistic model results suggest that competition with conifers may continue to affect oak distribution. For whitebark pine, projections by mechanistic vegetation models do not rule out the species' continued existence; however, known sensitivities, such as a reliance on snowpack, and projections from niche models indicate that the presence of whitebark pine in the Pioneer–Craters landscape is at risk. Finally, the vegetation models we reviewed showed fundamentally different futures for sagebrush steppe on the Plateau, varying from large-scale conversion to desert scrublands, to conversion to grassland, to increased conifer encroachment.

Not surprisingly, more information does not necessarily lead to greater certainty. Nonetheless, model results that initially appear to conflict can have reasonable explanations and identify specific management strategies. For example, climatic conditions for both Oregon white oak and sagebrush steppe are projected to remain suitable within portions of each focal landscape. However, mechanistic models suggest that competitive interactions could exclude these species from their respective regions. In such a scenario, the target species might be conserved by monitoring and potentially removing competitors. Similarly, although the overall picture for whitebark pine indicates declining habitat suitability, protecting small pockets of cool microrefugia – such as north-facing slopes or local depressions as described in Dobrowski (2011) – coupled with careful management could maintain the presence of the species in the Pioneer–Craters region. It is more challenging to interpret the divergent projections from the two mechanistic vegetation models for Oregon white oak and sagebrush steppe, because the models used different climate projections and vegetation classifications as well as different modeling approaches. The variability of these results highlights the need for more targeted modeling. In general, rigorous comparisons of vegetation models are needed to improve our understanding of these models and of vegetation dynamics. Finally, modeling results will be most useful if data producers can give context for their results and actively work with managers and other users to interpret findings.

Overall, these case studies demonstrate that no single information source will universally be the "best" or most useful, but rather that different data sources can improve understanding of different aspects of vulnerability. Whereas consensus can build confidence in projections, disagreement may result in important insights as to which aspects of vulnerability are most uncertain and at what scales. Indeed, disagreement may be valuable if it highlights systems or elements of systems that are particularly sensitive to differences in projected climate changes. Finally, provided that they are evaluated in light of their strengths and limitations, divergent projections can help managers visualize a wide range of potential climate impacts and future conditions, and lead to the development of more flexible and robust adaptation strategies. As managers set out to revise their current management practices, vulnerability assessments, and climate adaptation strategies, they will need to incorporate new data, models, and newly identified climate impacts. Developing familiarity with different information resources and promoting the skills to piece them together will be critical for planners and managers seeking to understand and anticipate future ecological responses to climate change.

Acknowledgements

Funding for this project was provided by the North Pacific and Great Northern Landscape Conservation Cooperatives. We thank all of the participants in the case study workshops and particularly D Patte, S Hall, and T O'Sullivan who contributed their knowledge and expertise to the case study development. We also thank T Nogeire for assistance with the sagebrush steppe case study.

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