Agreement and Uncertainty among Climate Change Impact Models: A Synthesis of Sagebrush Steppe Vegetation Projections☆

Authors: Zimmer, Scott N., Grosklos, Guenchik J., Belmont, Patrick, and Adler, Peter B.

Source: Rangeland Ecology and Management, 75(1) : 119-129

Published By: Society for Range Management

URL: https://doi.org/10.1016/j.rama.2020.12.006

Rangeland Ecology & Management 75 (2021) 119–129

Contents lists available at ScienceDirect

Rangeland Ecology & Management

journal homepage: www.elsevier.com/locate/rama

Agreement and Uncertainty Among Climate Change Impact Models: A Synthesis of Sagebrush Steppe Vegetation Projections[☆]

Scott N. Zimmer[a,d,*], Guenchik J. Grosklos[b,d], Patrick Belmont[c,d], Peter B. Adler[a,d]

[a] Department of Wildland Resources and the Ecology Center, Utah State University, Logan, UT 84322, USA
[b] Department of Mathematics and Statistics, Utah State University, Logan, UT 84322, USA
[c] Department of Watershed Science and the Ecology Center, Utah State University, Logan, UT 84322, USA
[d] Climate Adaptation Science Program, Utah State University, Logan, UT 84322, USA

ARTICLE INFO

Article history:
Received 4 October 2019
Revised 1 December 2020
Accepted 9 December 2020

Keywords:
Bureau of Land Management
cheatgrass
forage
model comparison
pinyon-juniper
sagebrush

ABSTRACT

Ecologists have built numerous models to project how climate change will impact rangeland vegetation, but these projections of future changes are difficult to validate, making their utility for land management planning unclear. In the absence of direct validation, researchers can ask whether projections from different models are consistent. High consistency across models, especially those based on different assumptions, would increase confidence in using projections for planning. Here, we analyzed 19 models of climate change impacts on sagebrush (*Artemisia tridentata* Nutt.), cheatgrass (*Bromus tectorum* L.), pinyon-juniper (*Pinus* L. spp. and *Juniperus* L. spp.), and forage production on Bureau of Land Management (BLM) lands in the US Intermountain West. These models consistently projected the potential for pinyon-juniper declines and forage production increases. In contrast, models of cheatgrass mainly projected no climate change impacts, while sagebrush models projected no change in most areas and declines in southern extremes. In most instances, vegetation projections from high- and low-emission scenarios differed only slightly.

The projected vegetation impacts have important management implications for agencies such as the BLM. Pinyon-juniper declines would reduce the need to control pinyon-juniper encroachment, and increases in forage production could benefit livestock and wildlife populations in some regions. Sagebrush conservation and restoration projects may be challenged in areas projected to experience sagebrush declines. Similar projections from high- and low-emission scenario models may increase confidence to consider model projections in planning. However, projected vegetation impacts may also interact with increasing future wildfire risk in ways single-response models do not anticipate. In particular, forage production increases could increase management challenges related to fire.

Introduction

Background

Ecological impacts of climate change, including shifts in species distribution, abundance, and phenology, have been widely documented across ecosystems and are predicted to intensify (Parmesan and Yohe 2003; Parmesan 2006; Urban 2015). However, forecasting specific impacts of climate change on given ecosystems remains extremely difficult. Predictive modeling techniques are commonly used to project climate change impacts, and while these models may be estimated with sophisticated statistical methods, quantifying the accuracy and uncertainty of decade-to-century-scale future projections most useful in climate change planning is extremely difficult (Araújo et al. 2005). As a result, the accuracy of long-term projections concerning ecological impacts of climate change is largely unknown (Knutti 2008), raising questions about their value for land management and planning (Robinson et al. 2008; Littell et al. 2011; Mouquet et al. 2015; Yates et al. 2018; Brice et al. 2020).

In the absence of direct model validation, models can be compared to evaluate consistency among their projections. If models reach similar conclusions despite differences in methods, input data, or assumptions, projections become more credible and

---

[☆] This work was supported by the National Science Foundation (grant 1633756) and The Wilderness Society. Funding sources did not have direct involvement in data collection, analysis, writing, or publication.

[*] Correspondence: Scott N. Zimmer, Dept of Wildland Resources and the Ecology Ctr and Climate Adaptation Science Program, Utah State University, Logan, UT 84322, USA.

E-mail address: scottnzimmer@gmail.com (S.N. Zimmer).

https://doi.org/10.1016/j.rama.2020.12.006
1550-7424/

less uncertain, and decision makers may be more confident considering them in planning. Such model intercomparison is a common approach among climate models. The Coupled Model Intercomparison Project (CMIP) (Eyring et al. 2016) and Ocean Model Intercomparison Project (OMIP) (Griffies et al. 2016) are notable model efforts synthesizing general circulation models (GCMs) and earth systems models to better project future climate changes. However, similar efforts focused on modeling the ecological impacts of climate change are rare (Krysanova and Hattermann 2017). Renwick et al. (2018) modeled climate change impacts on sagebrush through four approaches to evaluate consistency across models, and others have used multiple methods to model climate change impacts on stream fish in France (Buisson et al. 2010) and vegetation in California (Crimmins et al. 2013). However, such comparisons remain exceptions.

Meta-analysis, in which the results of independent studies are compared (Arnqvist and Wooster 1995), offers another form of model comparison especially well-suited for synthesizing results from multiple research groups and eliminating the potential bias of a single group conducting analyses. However, we know of only one climate change impact model meta-analysis focused on natural resources, a study that assessed overall ecosystem-level vulnerability of marine environments to climate change (Queirós et al. 2016).

Here, we synthesized projections from models of climate change impacts on four keystone vegetation components of the US Intermountain West—sagebrush (*Artemisia tridentata* Nutt.), cheatgrass (*Bromus tectorum* L.), pinyon-juniper (*Pinus* L. spp. and *Juniperus* L. spp.), and forage production. We compared model results using a spatially explicit vote-counting approach (Koricheva & Gurevitch 2013), revealing instances of high and low agreement in the direction of projected impacts throughout the Intermountain West. Vote-counting approaches are subject to several limitations compared with meta-analyses, including inability to account for differences in uncertainty between models. However, the approach was reasonable for this analysis because relative uncertainty of studies was not available and all model outputs (including changes in species presence/absence) could not be compared in a meta-analysis. We intended for this unique synthesis of climate change impact models to inform land management by addressing individual vegetation components at scales relevant to land managers, incorporating results from multiple researchers, and explicitly addressing agreement between studies.

BLM land and vegetation

We conducted this analysis specifically to address climate change impacts on Bureau of Land Management (BLM) lands within the US Intermountain West. The BLM manages approximately 142 million acres in this region and has a “multiple-use mandate” to administer land for livestock grazing, hunting, recreation, energy extraction, and other land uses (Bureau of Land Management 2016). Vegetation is the foundation for many of these uses, providing forage for domestic livestock and wildlife, habitat for wildlife, and other ecosystem services including protecting soils from erosion, sequestering carbon, and cycling nutrients (Havstad et al. 2007; Yapp et al. 2010).

Major land management issues exist in this area, including the spread of invasive species such as cheatgrass (Knapp 1996; Bradley 2009), encroachment of conifers such as pinyon-juniper into low-elevation habitats (Weisberg et al. 2007), and declines in sagebrush (Bradley 2010), which affect fire, grazing management, and wildlife habitat (Beschta et al. 2013). There is also difficulty balancing grazing and other land uses while maintaining habitat quality (Camp et al. 2014). The sagebrush-obligate sage-grouse *(Centrocercus urophasianus)* has received much recent attention, as suitable habitat declines increasingly threaten its populations (Creutzburg et al. 2015). Wildfire is a significant process in sagebrush steppe ecosystems, limiting establishment of woody perennials (Baker 2006; Davies et al. 2012; Chambers et al. 2014) and creating positive feedbacks with cheatgrass (Balch et al. 2013). Understanding how climate change will increasingly interact with these issues is crucial for land management planning.

Research objectives

Though various peer-reviewed studies have modeled future climate change impacts to vegetation components of the Intermountain West, we know of no efforts to compare their results to synthesize findings and assess agreement between studies. We aim to do such a synthesis to address the following objectives:

1. Review the projected future impacts of climate change on sagebrush, pinyon-juniper, cheatgrass, and forage production in the US Intermountain West, according to recently published vegetation models.
2. Assess whether projected impacts are consistent across models and whether differences in emissions scenarios influence projected impacts.
3. Interpret the management implications of projected vegetation impacts.

Methods

Study area

Our research was focused on BLM land in the US Intermountain West, defined as the region between the eastern slopes of the Rocky Mountains and the eastern slopes of the Sierra Nevada and Cascade Mountains, stretching from the Mexican to Canadian border. BLM land in this region encompasses ≈142 million acres across Washington, Oregon, California, Idaho, Nevada, Utah, Arizona, Montana, Wyoming, Colorado, and New Mexico, comprising more than one-quarter of the total area of the Intermountain West (**Fig. 1**). The Intermountain West includes 18 Environmental Protection Agency level III ecoregions (US EPA 2015), but BLM land falls predominantly in only four—the Northern Basin and Range (NBR), Central Basin and Range (CBR), Wyoming Basin (WB), and Colorado Plateau (CP). Since these regions are most significant to the management of Intermountain West BLM land, we focused only on those regions.

Obtaining vegetation model projections

We first conducted a literature review by searching Google Scholar for peer-reviewed studies modeling climate change impacts on sagebrush, cheatgrass, pinyon-juniper, and forage production in the Intermountain West. We searched each vegetation type in conjunction with the phrase “climate change,” as well as “projections,” “impacts,” “models,” and “forecasts” to find such studies. We selected 14 studies published since 2008 that provided spatially explicit results of projected impacts to these vegetation types due to climate change. The time constraint was selected to eliminate studies using outdated GCMs or methods. For each model, we noted important metadata, such as the model type, emissions scenarios considered, response variables, and the latest time to which results were modeled, since these characteristics may affect comparability of model projections. Spatial extents of the studies differed, but all studies addressed lands within the Intermountain West.

In all, we identified three studies addressing sagebrush (Schlaepfer et al. 2012; Still and Richardson 2015; Renwick et al. 2018), three addressing cheatgrass (Bradley 2009; Boyte et al. 2016; Brummer et al. 2016), five addressing pinyon-juniper

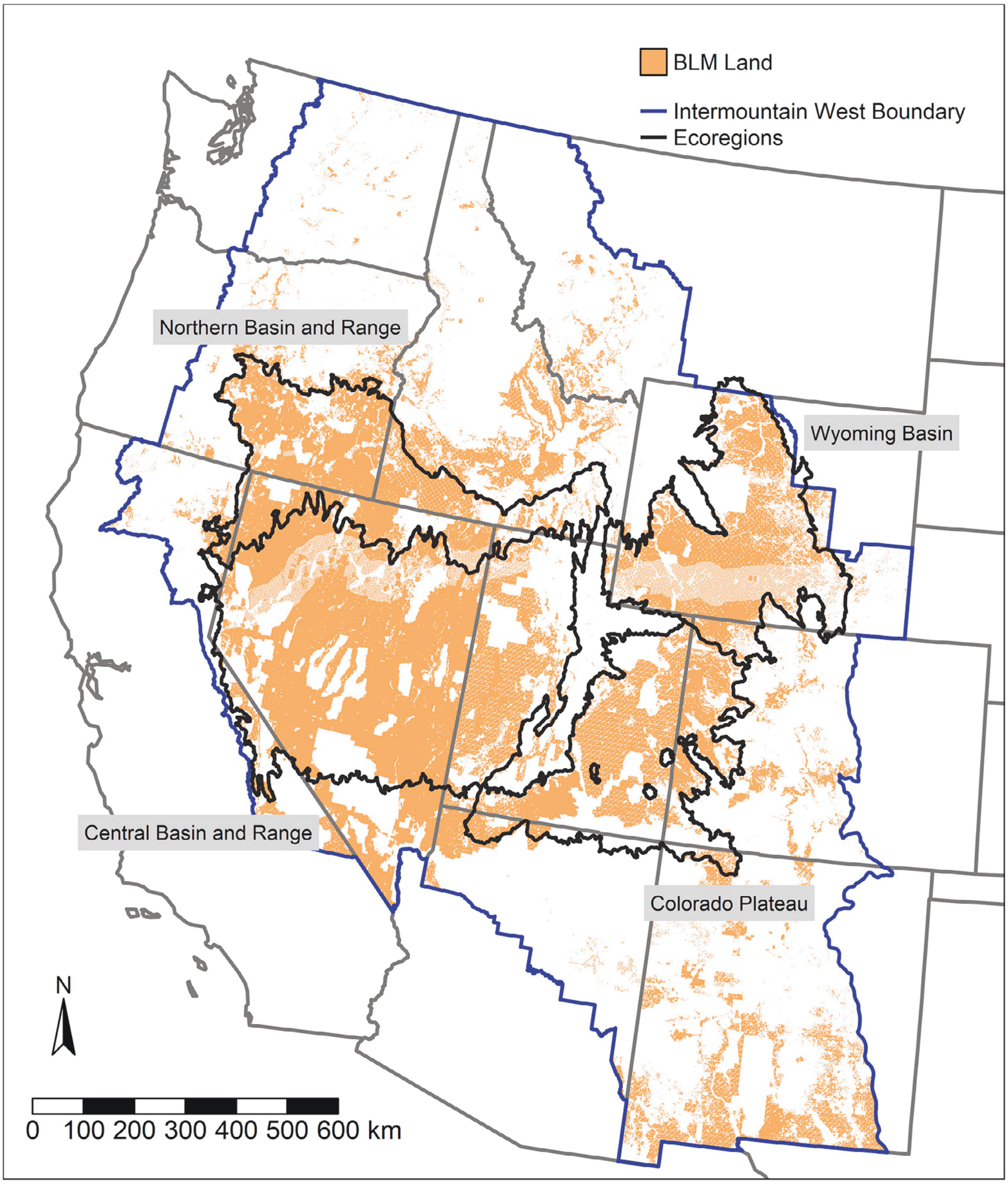

Fig. 1. Map of Bureau of Land Management (BLM) lands within the US Intermountain West. The four ecoregions containing the majority of BLM land in the Intermountain West are outlined and labeled.

(Cole et al. 2008; Notaro et al. 2012; Rehfeldt et al. 2012; Jiang et al. 2013; McDowell et al. 2016), and three addressing forage production (Notaro et al. 2012; Hufkens et al. 2016; Reeves et al. 2017). Many studies made multiple projections, employing either different emissions scenarios or model types. From the 14 studies, we obtained 19 models and 42 distinct projections of change for these vegetation components. Metadata for these studies are shown in **Table 1**.

The models we found can be broadly categorized as either correlations based, including spatial and temporal correlations, or process based. Spatial correlation models correlate current species distributions or abundances to current climatic and environmental conditions and predict future distribution based on projected future climate (Elith and Leathwick 2009). Temporal correlations models relate the effects of current interannual climatic variation to ecological responses and project these relationships using future climate (Kleinhesselink and Adler 2018). Process-based models consider the mechanistic processes driving system dynamics in order to project impacts of changing climate (Johnsen et al. 2001; Larocque et al. 2016). Broadly, process models explicitly define mechanistic model parameters, whereas these mechanisms are implicit in correlations models (Dormann et al. 2012).

The process-based models included in our study varied widely and used numerous distinct model programs, such as PhenoGrass (Hufkens et al. 2016), BIOME-BGC (Reeves et al. 2017), MC2 (Reeves et al. 2017), CNDV (Jiang et al. 2013), CESM (McDowell et al. 2016), and LPJ-GUESS (Notaro et al. 2012; Renwick et al. 2018). The spatial and temporal correlation models we used projected climate-related vegetation changes using random forest (Rehfeldt et al. 2012; Still and Richardson 2015; Renwick et al. 2018), boosted regression trees (Boyte et al. 2016; Brummer et al. 2016), Mahalanobis distance (Bradley 2009), or ensembles (Schlaepfer et al. 2012).

Since forage represents vegetation available for grazing, rather than a particular species, forage was modeled differently depending on the study. Forage production can be represented as grass-

Table 1
Studies from which model results were analyzed, showing metadata for model comparison. A1b, A2, and RCP 8.5 emissions scenarios were considered high emissions. B1, B2, and RCP 4.5 were considered low emissions. Results from Renwick et al. 2018 are supplemental results obtained from authors. Time of projection shows either the year or time span that was compared with reference conditions in each study.

Vegetation component	Study	Model type	Modeling method	Response variable(s)	Emissions scenario(s)	Time of projection	Wildfire included?	Figure(s)
Cheatgrass	Boyte et al. 2016	Spatial correlations	Boosted regression tree	Cover	Low	2061-2080	No	10
	Bradley 2009	Spatial correlations	Mahalanobis distance	Presence	High	2090-2100	No	7, 8a, 8b, 9
	Brummer et al. 2016	Spatial correlations	Boosted regression tree	Cover	Low	2061-2080	No	5c
Forage production	Hufkens et al. 2016	Process	PhenoGrass	Grass cover; gross primary productivity	High	2090-2100	No	2a (in text); 7k (supplemental material)
	Notaro et al. 2012	Process	LPJ-GUESS DGVM	Grass cover	High, Low	2000-2100	Yes	4c,4i,4o
	Reeves et al. 2017	Process	Biome-BGC	Net primary productivity	High, Low	2100	No	2a,2b,2c (supplementary material)
	Reeves et al. 2017	Process	MC2	Non-woody cover	High, Low	2100	Yes	3a,3b,3c (supplementary material)
Pinyon-juniper	Cole et al. 2008	Spatial correlations	Multiple quadratic logistic regression	Presence	High	~2100	No	5
	Jiang et al. 2013	Process	CNDV	Presence	High	2070-2099	Yes	5b
	McDowell et al. 2015	Process	CESM	Cover	High	2100	No	4h
	Notaro et al. 2012	Process	LPJ-GUESS DGVM	Cover	High, Low	2000-2100	Yes	4d,4j,4p
	Rehfeldt et al. 2012	Spatial correlations	Random forest	Presence	High, Low	2086-2095	No	3h,3i,3o,3p,3s,3t
Sagebrush	Renwick et al. 2018	Spatial correlations	Random forest	Cover	High, Low	2070-2099	No	N/A
	Renwick et al. 2018	Temporal correlations	Mixed effects model	Cover	High, Low	2070-2099	No	N/A
	Renwick et al. 2018	Process	Seedling survival model	Seedling survival	High, Low	2070-2099	No	N/A
	Renwick et al. 2018	Process	LPJ-GUESS DGVM	Cover	High, Low	2070-2099	Yes	N/A
	Schlaepfer et al. 2012	Spatial correlations	Ensemble SDM fit to climate	Presence	High, Low	2070-2099	No	3a,3b
	Schlaepfer et al. 2012	Spatial correlations	Ensemble SDM fit to ecohydrology model	Presence	High, Low	2070-2099	No	3c,3d
	Still & Richardson 2015	Spatial correlations	Random forest	Presence	High	2040-2069	No	1

land cover (Notaro et al. 2012; Hufkens et al. 2016) or relative abundance of nonwoody vegetation (Reeves et al. 2017), but we also included two studies that modeled changes to primary productivity (Hufkens et al. 2016; Reeves et al. 2017), which can be interpreted as a change in forage quantity. Increases in primary productivity do not necessarily translate directly to forage increases, but unless increasing primary productivity comes with a loss of palatable vegetation, it indicates an increase in biomass available for grazers and therefore a likely increase in forage quantity.

We considered only the latest future projections from each study. Many studies reported mean changes from a time span (e.g., the mean of projections from 2070 to 2099) relative to baseline conditions. See Table 1 for a list of all studies and time spans of their projections. Most studies projected changes through the end of the 21st century, though some included broader time spans than others. Projections through earlier time frames or including mean change from broad time spans may indicate lesser climate change impacts than others, but direction of change is less likely to vary between time frames. Since we considered only direction of change, not magnitude, the impact of varying projection times should be insignificant.

Analyzing vegetation model projections

We analyzed the results of models in a spatially explicit framework by downloading the highest-resolution image available for each figure, importing those into ArcMap, and georeferencing them. Georeferencing applies a geographic projection to an image and aligns it with the area to which it corresponds by anchoring it at easily identifiable features. This process converted the image into a raster whose resolution was determined by the resolution of the original image. We then conducted an unsupervised classification in R (Hijmans and van Etten 2016; R Core Team 2018) to identify pixel groups in each raster and manually assigned these pixel groups values of −1, 0, or 1, corresponding to a projected decrease in the vegetation component, no change, or an increase, respectively. For example, if a given image visualized a decrease in sagebrush abundance as red pixels, the classification collected all red pixels into a group, which we assigned a value of −1.

Our approach allowed us to only analyze the direction of vegetation impacts, not the magnitude of impacts. This was acceptable because many models we included analyzed changes in presence/absence of vegetation (see Table 1), for which magnitude cannot be determined. Pixels not corresponding to vegetation impacts, such as background, text, and legends, were removed by assigning them a value of NA. Every raster was masked by a polygon layer of BLM land in the Intermountain West (US Geological Survey 2017) to eliminate unnecessary information. For each vegetation component, we resampled all rasters by nearest neighbor to the finest pixel resolution and then counted the number of models indicating an increase, decrease, or no change at each pixel for each vegetation type.

We then visualized the counts of models projecting decreases, increases, or no change as color-coded ternary plots (maps with RGB coloring), considering only pixels where at least three models had projections. In these plots, the number of models indicating

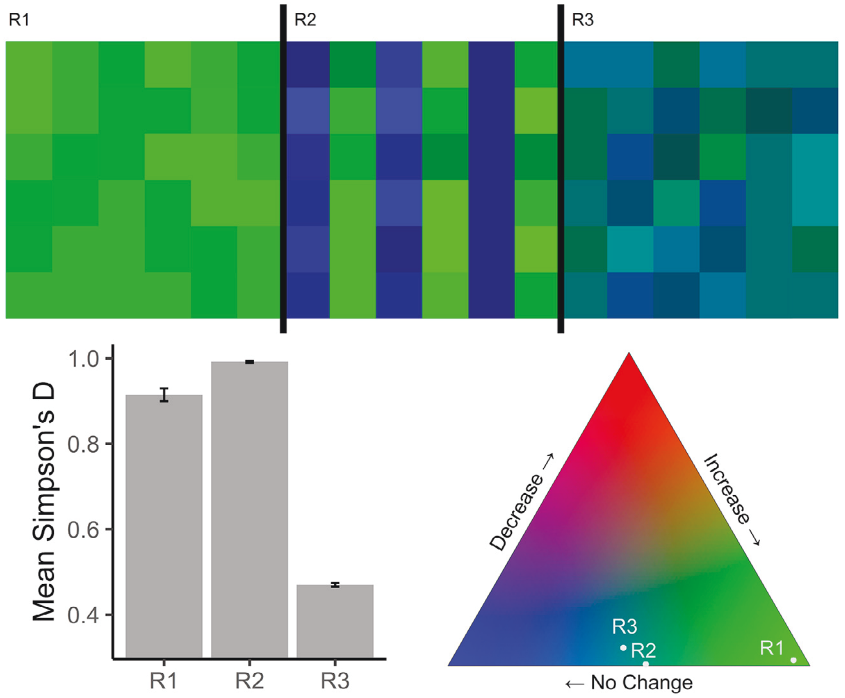

Fig. 2. Example of ternary plots in three regions. Red intensity is determined by the number of models indicating a decrease in vegetation, green intensity is determined by number of models indicating an increase, and blue intensity is determined by number of models indicating no change. Muted colors indicate more mixed projections. Mean pixel values of each region are shown in the ternary legend (white points with text labels), and mean Simpson's D for each region is shown in the barplot (with error bars indicating plus or minus the variance in Simpson's D throughout the region).

decreases in a vegetation type determined red intensity, number of models indicating an increase determined green intensity, and number of models indicating no change determined blue intensity. This visualization gave a broad sense of model projections on a pixel-by-pixel basis and revealed where models consistently projected a particular outcome or were split between multiple outcomes. This plot was complemented by a ternary legend showing the mean number of projections within each ecoregion (Smith 2017). An example of how these values were plotted onto the legend is shown in Figure S1 (available online at …). We made these visualizations showing all results for a given vegetation type, as well as results split by emissions scenario.

At each pixel, we also calculated Simpson's Diversity Index (Simpson's D) (Simpson 1949) to assess the diversity of model projections. This was a simple metric that allowed us to quantitatively assess whether multiple outcomes were projected at pixels or not. Since all pixels had three possible projections (increase, decrease, and no change), Simpson's D ranged from 0.33 to 1, with 0.33 representing maximum diversity of projections at a pixel (i.e., high uncertainty), and 1 representing minimum diversity (i.e., low uncertainty). We calculated mean Simpson's D in each ecoregion to assess the relative model uncertainty of pixels within each ecoregion and displayed this in barplots.

A hypothetical example of possible model projections is shown in **Fig. 2.** This example demonstrates the importance of both the ternary legend and Simpson's D in interpreting the ternary plot. Here, region 1 demonstrates high certainty increases at all pixels. This is reflected by the ternary legend, where the mean value for region 1 is strongly weighted toward increases, and by the high Simpson's D, indicating high certainty in this region. In both regions 2 and 3, the ternary legend shows mean values are split between increases and no change. However, region 2 has some pixels that strongly indicate increases and some that strongly indicate no change, whereas all pixels are split between these outcomes in region 3. This is an important distinction made clear by the Simpson's D barplot, which shows low Simpson's D (low certainty/high diversity) in region 3 and high Simpson's D (high certainty/low diversity) in region 2.

We did not assess the statistical significance of these outcomes for a number of reasons. First, the ternary plots communicate all the obtained information about the direction of change at individual pixels. Since we did not estimate any parameters or coefficients, it is not clear what additional information a *P* value would add. Second, while it is possible to test statistical significance at the level of individual pixels (e.g., chi-square or multinomial), the results would have low power due to small sample sizes, as small as three model projections at a given pixel. In addition, pixel-level tests would ignore spatial autocorrelation. We believe that the descriptive, visual results we produced are easier to interpret than a potentially flawed statistical analysis.

Results

We produced color-coded ternary plots revealing the overall projected impacts for each vegetation component on a pixel-by-pixel basis, along with ecoregion mean value and ecoregion mean Simpson's D (**Figs. 3–6**). These results were split to show results among models employing low emissions scenarios, high emissions scenarios, and across all emissions scenarios.

Pinyon-juniper projections showed decreases and were consistent across emissions scenarios in all ecoregions, except in WB (see Fig. 3). Decreases were strongest and most certain in NBR. Results in CBR and CP mainly showed decreases mixed with some indications of no change, as demonstrated by the mean values in these regions. Results in these regions also had lower certainty than results in NBR, evident from the lower Simpson's D in these regions. Emissions scenario strongly impacted results in WB, with low emissions scenarios showing high certainty increases

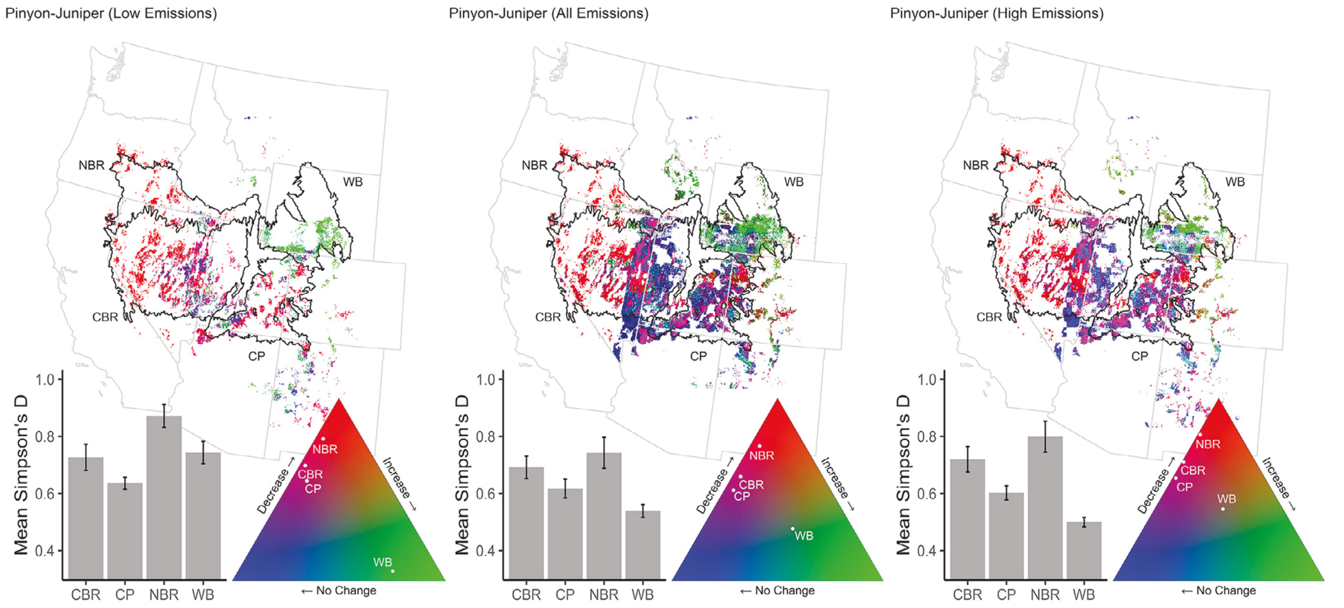

Fig. 3. Ternary plots, legends, and Simpson's D barplots for pinyon-juniper, among models employing low emissions scenarios, all emissions scenarios, and high emissions scenarios.

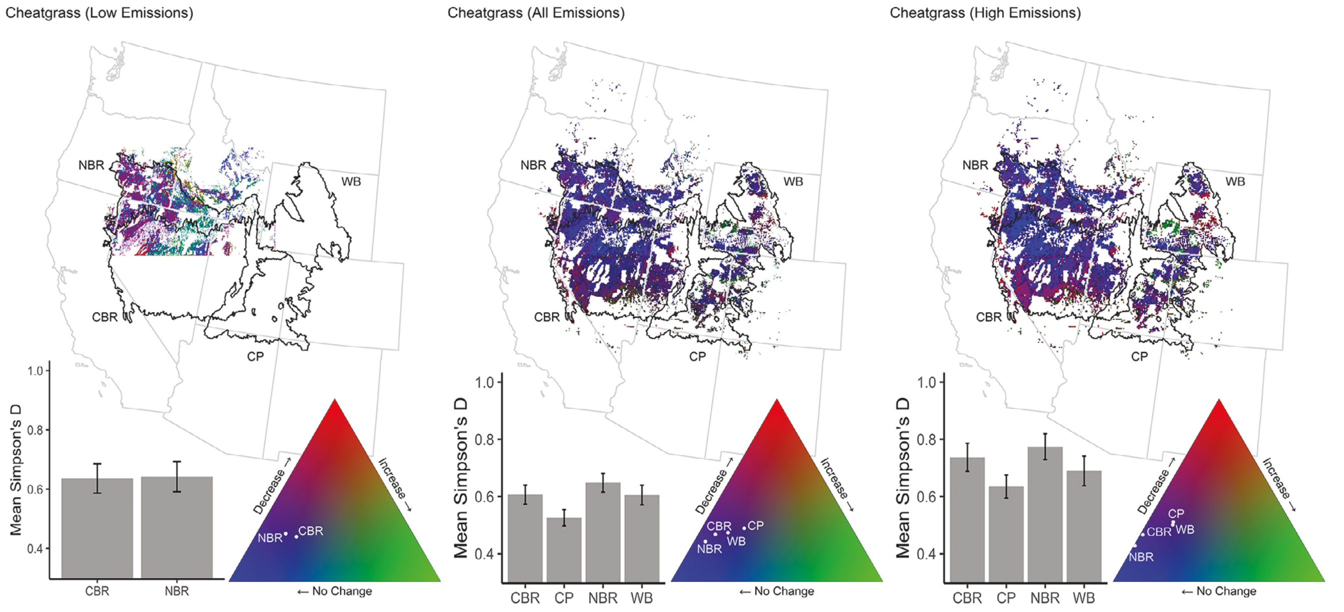

Fig. 4. Ternary plots, legend, and Simpson's D barplots for cheatgrass, among models employing low emissions scenarios, all emissions scenarios, and high emissions scenarios. Only two included models made cheatgrass projections under low emissions scenarios, so we included pixels addressed by both of those models. Results are not available for CP and WB because both models did not address these regions.

in this region. However, high emissions results in WB had uncertain and mixed results, with very low Simpson's D (high uncertainty) and a regional mean change value indicating a mix of all outcomes.

Cheatgrass tended toward no change in all ecoregions and did not vary by emissions scenario (see Fig. 4). In NBR and CBR, both low and high emissions results mainly had indications of no change, though low emissions results were slightly less certain and more mixed than high emissions results in these regions (lower Simpson's D and more mixed mean results). Results in CP and WB also tended toward no change but were slightly more uncertain and mixed, particularly in CP. There were insufficient models employing low emissions scenarios within CP and WB, so low emissions results were not available in these regions.

Forage production results varied by emissions scenario, with high emissions results indicating increases in all ecoregions, while low emissions results were more mixed between increases and no change (see Fig. 5). However, Simpson's D was similar or slightly higher for low emissions, meaning the more mixed results for low emissions reflect more spatial heterogeneity in results, not lower certainty. This means under low emissions, some locations showed increases with fairly high certainty, while others showed no change with high certainty.

Sagebrush results were consistent across emissions scenarios, showing either no change or decreases (see Fig. 6). In WB and NBR, results consistently indicated no change for both high and low emissions scenarios. Results were more mixed in CBR and CP, split between no change and decreases. Certainty was very high

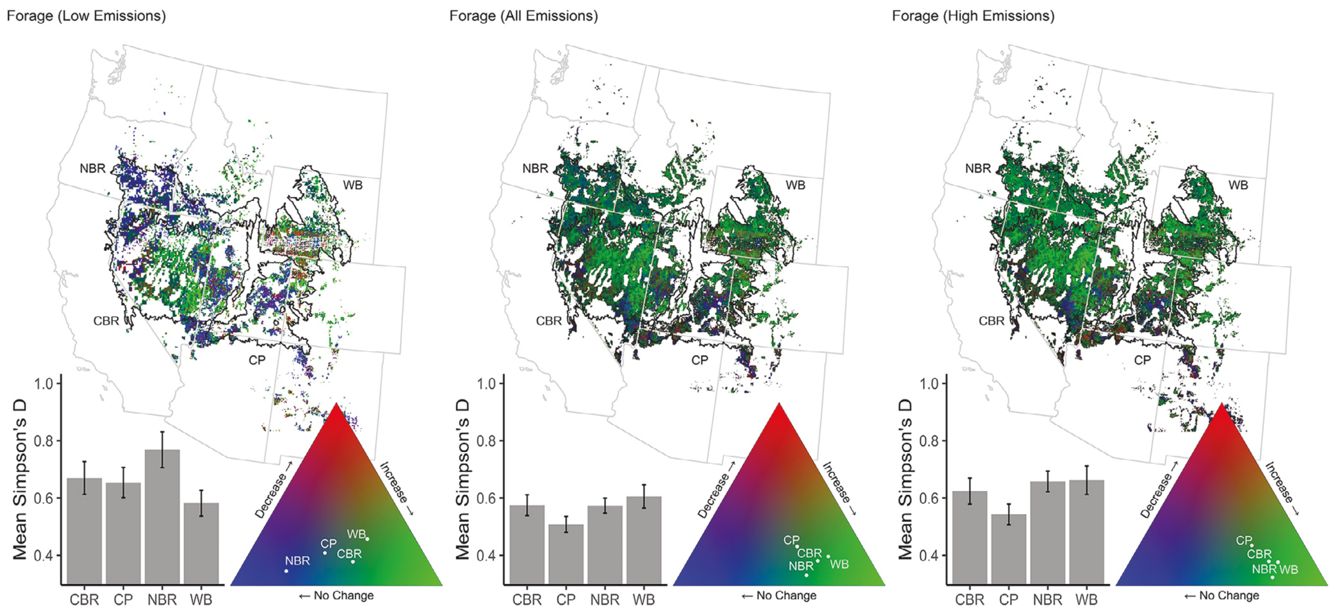

Fig. 5. Ternary plots, legends, and Simpson's D barplots for forage production, among models employing low emissions scenarios, all emissions scenarios, and high emissions scenarios.

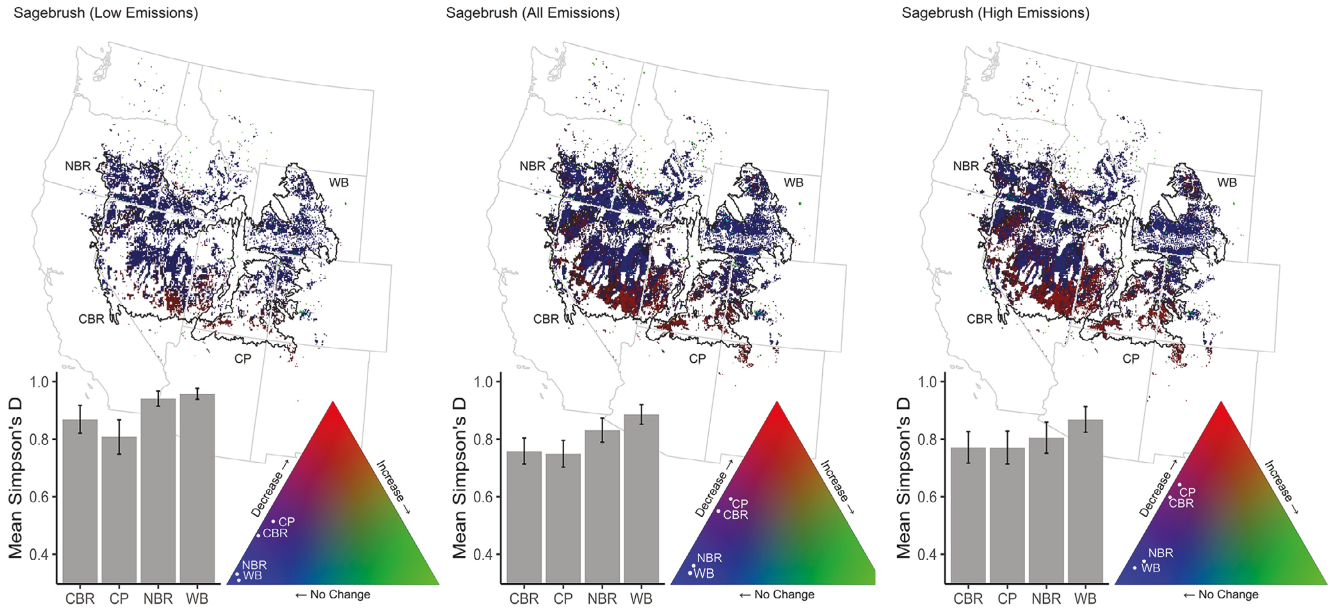

Fig. 6. Ternary plots, legends, and Simpson's D barplots for sagebrush, among models employing low emissions scenarios, all emissions scenarios, and high emissions scenarios.

in all ecoregions, as indicated by the high Simpson's D. Latitude seemed to strongly affect sagebrush results, as southern areas of these regions indicated decreases regardless of emissions scenario, and northern areas consistently showed no change. The high Simpson's D demonstrates that though results were more mixed overall in CBR and CP, there was still high certainty.

Our sagebrush analysis included nongridded, point projections from one study with four models (Renwick et al. 2018). To include these points in our analysis, we analyzed them as individual raster cells, but these covered little area and thus had little weight. When we considered only the cells included in Renwick et al., results differed slightly (Fig. S2, available online at …), suggesting sagebrush may increase in many places where Fig. 6 indicated no change. However, the Renwick et al. subset was consistent with the full analysis in indicating sagebrush declines in its southern range.

Discussion

Projected vegetation changes

In this study, we aggregated results of studies that modeled climate change impacts on different vegetation types in the Intermountain West and summarized these results with color-coded ternary plots. These plots help show where models agree and disagree on the direction of projected vegetation impacts, providing a sense of overall consistency among the studies.

The pervasive pinyon juniper declines indicated in our analysis, particularly in the Northern and Central Basin and Range, agree with reviews that have argued for widespread tree mortality in a warmer future (van Mantgem et al. 2009; Allen et al. 2015). However, our results differed regionally, with uncertain, mixed projections overall in the Wyoming Basin. This region is a distinct spur of sagebrush steppe with a cool/moist soil moisture and temperature regime (Chambers et al. 2014), where climate change impacts on pinyon-juniper may not be as negative as in the other ecoregions.

We found that cheatgrass projections tended toward no change and were somewhat mixed and uncertain in the Colorado Plateau in particular. Some experimental studies have suggested cheatgrass may benefit from climate change at local scales (Ziska et al. 2005; Zelikova et al. 2013; Compagnoni and Adler 2014), somewhat at odds with the models we reviewed. This discrepancy could be due to the strong association of cheatgrass with local disturbance and local soil resources (Bradford and Lauenroth 2006; Chambers et al. 2007), which potentially restricts the ability to model direct and indirect impacts of climate change on cheatgrass at regional scales.

Our forage results mainly showed forage production increases, which were stronger under high emissions. This agrees with much of the literature, which anticipates increases in forage production largely due to increased CO_2 concentrations (Izaurralde et al. 2011; Polley et al. 2013; Friend et al., 2014). Under low emissions scenarios CO_2 enrichment is less pronounced, potentially explaining the more mixed projections among low emissions results.

Our sagebrush projections showed consistent decreases in the southern portions of the Central Basin and Range and Colorado Plateau while consistently indicating no change elsewhere. These results support expectations of sagebrush declines in the southern range and lower elevations but do not agree with predictions of increases in its northern range and higher elevations (Bradley 2010; Kleinhesselink and Adler 2018). These areas are predominantly not managed by BLM, though, and as such are not included in our analysis.

Emissions scenario uncertainty

Model projections under different emissions scenarios provide insight into how vegetation impacts may differ given different future emissions trajectories. Uncertainty in emissions trajectories may complicate climate change adaptation planning (Dessai and Hulme 2007), but the importance of emissions trajectories in planning is reduced if projected impacts are consistent across emissions scenarios.

We generally found a high degree of agreement in projected impacts from models employing different emissions scenarios. While we were not able to assess the magnitude of projected vegetation impacts, which may be more sensitive to emissions scenario, we found that in most cases the direction of projected impacts was not strongly influenced by emissions scenarios in our study area. Therefore, management actions can potentially be planned despite uncertainty in future emissions trajectories, as we expect similar shifts for these vegetation types regardless of emissions scenario.

However, we found conflicting results depending on emissions scenarios in a handful of cases. High emissions scenarios indicated forage production increases in all regions, but low emissions scenarios indicated no impacts in the Northern Basin and Range and more mixed results in the Colorado Plateau. Pinyon-juniper projections in the Wyoming Basin were also influenced by emissions scenario, with low emissions indicating increases and high emissions showing uncertain, mixed results. In these instances, overall projections should be seen as more uncertain, given the potential for differing outcomes depending on emissions scenarios.

Model choice uncertainty

We considered two sources of model choice uncertainty. First, models differ in broad approach, such as process-based versus spatial or temporal correlations. Second, studies using the same approach, such as spatial correlations, employ varying statistical methods that influence predictions. For example, an evaluation of 33 species distribution models found statistical methods strongly influenced predictive performance (Norberg et al. 2019), and others have found fitting method can affect distribution model results more than emissions scenario or GCM (Diniz-Filho et al. 2009; Buisson et al. 2010).

Therefore, a consensus in projected impacts from models using contrasting approaches and statistical methods increases confidence in projections. On the other hand, a consensus in projections from models based on similar approaches may be less meaningful, since any single approach may have biases toward a given result.

Across the models we studied, there was variation in the diversity of approaches and methods. For example, the cheatgrass models we found had no diversity of approach since all were spatial correlations models and had little diversity in statistical methods, with two modeling cover through boosted regression trees while one modeled presence/absence with Mahalanobis distance (see Table 1). This limited ensemble may therefore underestimate model choice uncertainty. Similarly, we found only process-based models of forage production. However, each of these studies used a different simulation model (e.g., Biome-BGC, MC2) and response variables also differed between models (grass cover, nonwoody vegetation cover, gross primary productivity, and net primary productivity), making this suite of models more diverse. Pinyon-juniper and sagebrush had the most varied ensembles—process and correlations models were available for each of these vegetation types, and modeling methods and response variables also differed between models. This diversity increases our confidence in the projections. Despite the diversity of these ensembles, we did not find that pinyon-juniper and sagebrush projections were more inconsistent than those for cheatgrass or forage production.

Limitations

We employed a research synthesis of projected vegetation models using vote-counting methods of categorical projected changes. Although vote counting provides a simple method to quantitatively summarize published results, it comes with disadvantages (Koricheva & Gurevitch 2013). First, our method used downloaded images from each study and categorized each pixel into one of three categories. This disregards the difference in magnitudes of projections reported in the original studies. Secondly, our method weighted each reported pixel evenly, ignoring different time span projections and wildfire scenarios. These factors could have different effects on our categorization methods, including reported magnitudes and model uncertainties. That being said, these are unavoidable difficulties when summarizing different model types and model variables. Considering these challenges, we opted for simple metrics that provide the greatest transparency to provide a clear synthesis of model projections.

There is inherent uncertainty in projecting future climate (Deser et al. 2012), and this uncertainty carries over into any models projecting ecological impacts of climate change. These models are complex but cannot consider all possible drivers of ecological change. For example, increases in extreme weather events due to climate change are likely (Field et al. 2012) but may not be explicitly considered by many ecological impact models. Models account for interactions such as species competition or disturbance from wildfire or grazing in various ways, another limitation that can affect their generalizability.

Wildfire in particular may be important to consider in relation to our results. Increases in wildfire size, frequency, and intensity in response to climate change are expected in the Intermountain West (Barbero et al. 2015; Abatzoglou and Williams 2016; Murphy et al. 2018; Prudencio et al. 2018) due to warmer, drier conditions and excessive fuel loads (Liu and Wimberly 2016; Murphy et al. 2018). Projected forage production increases we found could intensify these wildfire dynamics as well. In the models we analyzed, forage represents either overall plant productivity or grass cover—increases in these measures indicate more total fuels or more fine fuels, respectively, either of which could promote wildfires.

Wildfire increases could greatly impact the vegetation we considered. Pinyon-juniper and sagebrush are extremely susceptible to fire (Allen et al. 2015; McDowell et al. 2016; Davies et al. 2012), meaning increased wildfire could encourage greater declines in pinyon-juniper and sagebrush than projected by the models we analyzed. Cheatgrass promotes and benefits from wildfire through the "cheatgrass-fire cycle" (Balch et al. 2013; Bradley et al. 2018), so increased wildfire could benefit cheatgrass beyond what was projected in the models we reviewed (Larson et al. 2018). Only four models we analyzed specifically accounted for wildfire (Jiang et al. 2013; Notaro et al. 2012; Reeves et al. 2017; Renwick et al. 2018), so wildfire interactions are not well accounted for in our results.

Implications

The potential for pinyon-juniper declines in the Colorado Plateau, Central Basin and Range, and Northern Basin and Range indicate there may be less need for pinyon-juniper management actions such as chaining and prescribed burns by the end of the 21st century. Such management actions have been widespread for decades to control pinyon-juniper encroachment (Redmond et al. 2013). We mainly found indications of no projected impacts to cheatgrass, indicating current cheatgrass management objectives should continue into the future. However, cheatgrass projections are strongly correlated with precipitation amount and seasonality (Bradley 2009), which remain difficult to project into the future. Therefore, cheatgrass projections could change as future precipitation predictions improve. Since other invasive grasses such as medusahead (*Taeniatherum caput-medusae* L.) and red brome (*Bromus rubens* L.) could fill the cheatgrass niche if it were to decline (Snyder et al. 2019), invasive grass management needs are likely to continue, though.

Projected forage increases could have major management implications, positively impacting livestock grazing and wildlife. However, overall management implications may be more complex, as climate change could also increase heat stress on livestock and wildlife and make forage production more variable (Reeves et al. 2017; Brice et al. 2020). Indications of no impacts on sagebrush in many areas indicate current sagebrush management can continue in the future through much of the Intermountain West. We did find the potential for sagebrush declines in southern parts of the Central Basin and Range and Colorado Plateau, though, implying that conservation and restoration investments in these areas may be risky. Wildfire is likely to become more intense and frequent due to climate change, which may interact with these vegetation impacts in direct and indirect ways we were not able to address.

Conclusion

We conducted a spatially explicit synthesis with vote-counting methods of models projecting climate change impacts to vegetation on BLM lands throughout the Intermountain West. We found many instances where climate change is projected to impact vegetation, and the direction of these impacts were generally consistent across high and low emissions scenarios. These projected impacts have implications for future management of BLM lands, and the general agreement between high and low emissions results indicates that planning can proceed despite uncertainty in future emissions trajectories.

Projections of the ecological impacts of climate change are inherently uncertain, given the complexity of ecological systems and the uncertainty of future climate projections and emissions scenarios. Researchers address these uncertainties through different approaches, modeling techniques, and parameter fitting. Such methodological diversity is constructive, as it enables the scientific community to explore uncertainties and potential biases from given approaches. Syntheses of related studies like ours are useful tools to determine where projections are consistent despite uncertainty and model variation, where they may reliably inform policy and management and where conflicts among projections may need to be reconciled.

Declaration of Competing Interest

None.

Acknowledgments

We would like to thank all students and faculty within the Climate Adaptation Science program for help encouraging our research and refining our ideas. Courtney Flint provided essential support throughout the project, as did Elaine Brice, Kirsten Goldstein, Brett Miller, and Hongchao Zhang. Thank you to Nancy Huntly for continued guidance and support of the Climate Adaptation Science program and to Hadia Akbar, Rachel Hager, Tara Saley, and Emily Wilkins for feedback on our project. We also would like to thank the journal reviewers, who helped us improve the project greatly.

Data availability

The underlying data and code used in this analysis are available online (Zimmer et al. 2020).

Supplementary materials

Supplementary material associated with this article can be found, in the online version, at doi:10.1016/j.rama.2020.12.006.

References

Abatzoglou, J.T., Williams, A.P., 2016. Impact of anthropogenic climate change on wildfire across western US forests. Proceedings of the National Academy of Sciences 113, 11770–11775.

Allen, C.D., Breshears, D.D., McDowell, N.G., 2015. On underestimation of global vulnerability to tree mortality and forest die-off from hotter drought in the Anthropocene. Ecosphere 6, art129.

Araújo, M.B., Pearson, R.G., Thuiller, W., Erhard, M., 2005. Validation of species—climate impact models under climate change. Global Change Biology 11, 1504–1513.

Arnqvist, G., Wooster, D., 1995. Meta-analysis: synthesizing research findings in ecology and evolution. Trends in Ecology & Evolution 10, 236–240.

Baker, W.L., 2006. Fire and restoration of sagebrush ecosystems. Wildlife Society Bulletin 34, 177–185.

Balch, J.K., Bradley, B.A., D'Antonio, C.M., Gómez-Dans, J., 2013. Introduced annual grass increases regional fire activity across the arid western USA (1980–2009). Global Change Biology 19, 173–183.

Barbero, R., Abatzoglou, J.T., Larkin, N.K., Kolden, C.A., Stocks, B., 2015. Climate change presents increased potential for very large fires in the contiguous United States. International Journal of Wildland Fire 24, 892.

Beschta, R.L., Donahue, D.L., DellaSala, D.A., Rhodes, J.J., Karr, J.R., O'Brien, M.H., Fleischner, T.L., Deacon Williams, C., 2013. Adapting to climate change on western public lands: addressing the ecological effects of domestic, wild, and feral ungulates. Environmental Management 51, 474–491.

Boyte, S.P., Wylie, B.K., Major, D.J., 2016. Cheatgrass percent cover change: comparing recent estimates to climate change−driven predictions in the northern Great Basin. Rangeland Ecology & Management 69, 265–279.

Bradford, J.B., Lauenroth, W.K., 2006. Controls over invasion of *Bromus tectorum:* The importance of climate, soil, disturbance and seed availability. Journal of Vegetation Science 17, 693–704.

Bradley, B.A., 2010. Assessing ecosystem threats from global and regional change: hierarchical modeling of risk to sagebrush ecosystems from climate change, land use and invasive species in Nevada, USA. Ecography 33, 198–208.

Bradley, B.A., 2009. Regional analysis of the impacts of climate change on cheatgrass invasion shows potential risk and opportunity. Global Change Biology 15, 196–208.

Bradley, B.A., Curtis, C.A., Fusco, E.J., Abatzoglou, J.T., Balch, J.K., Dadashi, S., Tuanmu, M.-N., 2018. Cheatgrass *(Bromus tectorum)* distribution in the intermountain Western United States and its relationship to fire frequency, seasonality, and ignitions. Biological Invasions 20, 1493–1506.

Brice, E.M., Miller, B.A., Zhang, H., Goldstein, K., Zimmer, S.N., Grosklos, G.J., Belmont, P., Flint, C.G., Givens, J.E., Adler, P.B., Brunson, M.W., Smith, J.W., 2020. Impacts of climate change on multiple use management of Bureau of Land Management land in the Intermountain West, USA. Ecosphere 11, e03286.

Brummer, T.J., Taylor, K.T., Rotella, J., Maxwell, B.D., Rew, L.J., Lavin, M., 2016. Drivers of *Bromus tectorum* abundance in the western North American sagebrush steppe. Ecosystems 19, 986–1000.

Buisson, L., Thuiller, W., Casajus, N., Lek, S., Grenouillet, G., 2010. Uncertainty in ensemble forecasting of species distribution. Global Change Biology 16, 1145–1157.

Bureau of Land Management. 2016. About: our mission [WWW document]. About: our mission. Available at: https://www.blm.gov/about/our-mission. Accessed 29 April, 2019.

Camp, M.J., Rachlow, J.L., Shipley, L.A., Johnson, T.R., Bockting, K.D., 2014. Grazing in sagebrush rangelands in western North America: implications for habitat quality for a sagebrush specialist, the pygmy rabbit. The Rangeland Journal 36, 151.

Chambers, J. C., Pyke, D. A., Maestas, J. D., Pellant, M., Boyd, C. S., Campbell, S. B., Espinosa, S., Havlina, D. W., Mayer, K. E., and Wuenschel, A. 2014. Using resistance and resilience concepts to reduce impacts of invasive annual grasses and altered fire regimes on the sagebrush ecosystem and greater sage-grouse: a strategic multi-scale approach. Gen. Tech. Rep. RMRS-GTR-326. Fort Collins, CO: U.S. Department of Agriculture, Forest Service, Rocky Mountain Research Station. 73 p.

Chambers, J.C., Roundy, B.A., Blank, R.R., Meyer, S.E., Whittaker, A., 2007. What makes Great Basin sagebrush ecosystems invasible by *Bromus tectorum?*. Ecological Monographs 77, 117–145.

Cole, K.L., Ironside, K.E., Arundel, S.T., Duffy, P., Shaw, J., 2008. Modeling future plant distributions on the Colorado Plateau: an example using *Pinus edulis*. In: van Riper, III, C., Sogge, M.K. (Eds.), The Colorado Plateau III. Integrating research and resources management for effective conservation. The University of Arizona Press, Tucson, AZ, USA, pp. 319–330.

Compagnoni, A., Adler, P.B., 2014. Warming, competition, and *Bromus tectorum* population growth across an elevation gradient. Ecosphere 5, art121.

Creutzburg, M.K., Halofsky, J.E., Halofsky, J.S., Christopher, T.A., 2015. Climate change and land management in the rangelands of central Oregon. Environmental Management 55, 43–55.

Crimmins, S.M., Dobrowski, S.Z., Mynsberge, A.R., 2013. Evaluating ensemble forecasts of plant species distributions under climate change. Ecological Modelling 266, 126–130.

Davies, G.M., Bakker, J.D., Dettweiler-Robinson, E., Dunwiddie, P.W., Hall, S.A., Downs, J., Evans, J., 2012. Trajectories of change in sagebrush steppe vegetation communities in relation to multiple wildfires. Ecological Applications 22, 1562–1577.

Deser, C., Phillips, A., Bourdette, V., Teng, H., 2012. Uncertainty in climate change projections: the role of internal variability. Clim Dyn 38, 527–546.

Dessai, S., Hulme, M., 2007. Assessing the robustness of adaptation decisions to climate change uncertainties: a case study on water resources management in the East of England. Global Environmental Change 17, 59–72.

Diniz-Filho, J.A.F., Mauricio Bini, L., Fernando Rangel, T., Loyola, R.D., Hof, C., Nogués-Bravo, D., Araújo, M.B., 2009. Partitioning and mapping uncertainties in ensembles of forecasts of species turnover under climate change. Ecography 32, 897–906.

Dormann, C.F., Schymanski, S.J., Cabral, J., Chuine, I., Graham, C., Hartig, F., Kearney, M., Morin, X., Römermann, C., Schröder, B., Singer, A., 2012. Correlation and process in species distribution models: bridging a dichotomy. Journal of Biogeography 39, 2119–2131.

Elith, J., Leathwick, J.R., 2009. Species distribution models: ecological explanation and prediction across space and time. Annual Review of Ecology, Evolution, and Systematics 40, 677–697.

Eyring, V., Bony, S., Meehl, G.A., Senior, C.A., Stevens, B., Stouffer, R.J., Taylor, K.E., 2016. Overview of the Coupled Model Intercomparison Project Phase 6 (CMIP6) experimental design and organization. Geoscientific Model Development 9, 1937–1958.

Field, C.B., Barros, V., Stocker, T.F., Dahe, Q., Dokken, D.J., Ebi, K.L., Mastrandrea, M.D., Mach, K.J., Plattner, G.-K., Allen, S.K., Tignor, M., Midgley, P.M., 2012. Managing the risks of extreme events and disasters to advance climate change adaptation. Special report of the intergovernmental panel on climate change. Cambridge University Press, Cambridge.

Friend, A.D., Lucht, W., Rademacher, T.T., Keribin, R., Betts, R., Cadule, P., Ciais, P., Clark, D.B., Dankers, R., Falloon, P.D., Ito, A., Kahana, R., Kleidon, A., Lomas, M.R., Nishina, K., Ostberg, S., Pavlick, R., Peylin, P., Schaphoff, S., Vuichard, N., Warszawski, L., Wiltshire, A., Woodward, F.I., 2014. Carbon residence time dominates uncertainty in terrestrial vegetation responses to future climate and atmospheric CO_2. Proceedings of the National Academy of Sciences 111, 3280–3285.

Griffies, S.M., Danabasoglu, G., Durack, P.J., Adcroft, A.J., Balaji, V., Böning, C.W., Chassignet, E.P., Curchitser, E., Deshayes, J., Drange, H., Fox-Kemper, B., Gleckler, P.J., Gregory, J.M., Haak, H., Hallberg, R.W., Heimbach, P., Hewitt, H.T., Holland, D.M., Ilyina, T., Jungclaus, J.H., Komuro, Y., Krasting, J.P., Large, W.G., Marsland, S.J., Masina, S., McDougall, T.J., Nurser, A.J.G., Orr, J.C., Pirani, A., Qiao, F., Stouffer, R.J., Taylor, K.E., Treguier, A.M., Tsujino, H., Uotila, P., Valdivieso, M., Wang, Q., Winton, M., Yeager, S.G, 2016. OMIP contribution to CMIP6: experimental and diagnostic protocol for the physical component of the Ocean Model Intercomparison Project. Geoscientific Model Development 9, 3231–3296.

Havstad, K.M., Peters, D.P.C., Skaggs, R., Brown, J., Bestelmeyer, B., Fredrickson, E., Herrick, J., Wright, J, 2007. Ecological services to and from rangelands of the United States. Ecological Economics 64, 261–268.

Hijmans, R.J., van Etten, J., 2016. Raster: Geographic data analysis and modeling. R package version 2.

Hufkens, K., Keenan, T.F., Flanagan, L.B., Scott, R.L., Bernacchi, C.J., Joo, E., Brunsell, N.A., Verfaillie, J., Richardson, A.D., 2016. Productivity of North American grasslands is increased under future climate scenarios despite rising aridity. Nature Climate Change 6, 710–714.

Izaurralde, R.C., Thomson, A.M., Morgan, J.A., Fay, P.A., Polley, H.W., Hatfield, J.L., 2011. Climate impacts on agriculture: implications for forage and rangeland production. Agronomy Journal 103, 371.

Jiang, X., Rauscher, S.A., Ringler, T.D., Lawrence, D.M., Williams, A.P., Allen, C.D., Steiner, A.L., Cai, D.M., McDowell, N.G., 2013. Projected future changes in vegetation in western North America in the twenty-first century. Journal of Climate 26, 3671–3687.

Johnsen, K., Samuelson, L., Teskey, R., McNulty, S., Fox, T., 2001. Process models as tools in forestry research and management. Forest Science 47 (1), 2–8.

Kleinhesselink, A.R., Adler, P.B., 2018. The response of big sagebrush *(Artemisia tridentata)* to interannual climate variation changes across its range. Ecology 99, 1139–1149.

Knapp, P.A., 1996. Cheatgrass (*Bromus tectorum* L) dominance in the Great Basin Desert: history, persistence, and influences to human activities. Global Environmental Change 6, 37–52.

Knutti, R., 2008. Should we believe model predictions of future climate change? Philosophical Transactions of the Royal Society A: Mathematical, Physical and Engineering Sciences 366, 4647–4664.

Koricheva, J., Gurevitch, J., 2013. 1. Place of meta-analysis among other methods of research synthesis. Princeton University Press, Princeton, NJ, USA, pp. 3–13.

Krysanova, V., Hattermann, F.F., 2017. Intercomparison of climate change impacts in 12 large river basins: overview of methods and summary of results. Climatic Change 141, 363–379.

Larocque, G.R., Komarov, A., Chertov, O., Shanin, V., Liu, J., Bhatti, J.S., Wang, W., Peng, C., Shugart, H.H., Xi, W., Holm, J.A., 2016. Process-Based Models: A Synthesis of Models and Applications to Address Environmental and Management Issues, Ecological Forest Management Handbook. CRC Press.

Larson, C.D., Lehnhoff, E.A., Noffsinger, C., Rew, L.J., 2018. Competition between cheatgrass and bluebunch wheatgrass is altered by temperature, resource availability, and atmospheric CO_2 concentration. Oecologia 186, 855–868.

Littell, J.S., McKenzie, D., Kerns, B.K., Cushman, S., Shaw, C.G., 2011. Managing uncertainty in climate-driven ecological models to inform adaptation to climate change. Ecosphere 2, art102.

Liu, Z., Wimberly, M.C., 2016. Direct and indirect effects of climate change on projected future fire regimes in the western United States. Science of The Total Environment 542, 65–75.

McDowell, N.G., Williams, A.P., Xu, C., Pockman, W.T., Dickman, L.T., Sevanto, S., Pangle, R., Limousin, J., Plaut, J., Mackay, D.S., Ogee, J., Domec, J.C., Allen, C.D., Fisher, R.A., Jiang, X., Muss, J.D., Breshears, D.D., Rauscher, S.A., Koven, C., 2016. Multi-scale predictions of massive conifer mortality due to chronic temperature rise. Nature Climate Change 6, 295–300.

Mouquet, N., Lagadeuc, Y., Devictor, V., Doyen, L., Duputié, A., Eveillard, D., Faure, D., Garnier, E., Gimenez, O., Huneman, P., Jabot, F., Jarne, P., Joly, D., Julliard, R., Kéfi, S., Kergoat, G.J., Lavorel, S., Gall, L.L., Meslin, L., Morand, S., Morin, X., Morlon, H., Pinay, G., Pradel, R., Schurr, F.M., Thuiller, W., Loreau, M., 2015. Predictive ecology in a changing world. Journal of Applied Ecology 52, 1293–1310.

Murphy, B.P., Yocom, L.L., Belmont, P., 2018. Beyond the 1984 perspective: narrow focus on modern wildfire trends underestimates future risks to water security. Earth's Future 6, 1492–1497.

Norberg, A., Abrego, N., Blanchet, F.G., Adler, F.R., Anderson, B.J., Anttila, J., Araújo, M.B., Dallas, T., Dunson, D., Elith, J., Foster, S.D., Fox, R., Franklin, J., Godsoe, W., Guisan, A., O'Hara, B., Hill, N.A., Holt, R.D., Hui, F.K.C., Husby, M., Kålås, J.A., Lehikoinen, A., Luoto, M., Mod, H.K., Newell, G., Renner, I., Roslin, T., Soininen, J., Thuiller, W., Vanhatalo, J., Warton, D., White, M., Zimmermann, N.E., Gravel, D., Ovaskainen, O, 2019. A comprehensive evaluation of predictive performance of 33 species distribution models at species and community levels. Ecological Monographs e01370.

Notaro, M., Mauss, A., Williams, J.W., 2012. Projected vegetation changes for the American Southwest: combined dynamic modeling and bioclimatic-envelope approach. Ecological Applications 22, 1365–1388.

Parmesan, C., 2006. Ecological and evolutionary responses to recent climate change. Annual Review of Ecology, Evolution, and Systematics 37, 637–669.

Parmesan, C., Yohe, G., 2003. A globally coherent fingerprint of climate change impacts across natural systems. Nature 421, 37–42.

Polley, H.W., Briske, D.D., Morgan, J.A., Wolter, K., Bailey, D.W., Brown, J.R., 2013. Climate change and North American rangelands: trends, projections, and implications. Rangeland Ecology & Management 66, 493–511.

Prudencio, L., Choi, R., Esplin, E., Ge, M., Gillard, N., Haight, J., Belmont, P., Flint, C., 2018. The impacts of wildfire characteristics and employment on the adaptive management strategies in the Intermountain West. Fire 1, 46.

Queirós, A.M., Huebert, K.B., Keyl, F., Fernandes, J.A., Stolte, W., Maar, M., Kay, S., Jones, M.C., Hamon, K.G., Hendriksen, G., Vermard, Y., Marchal, P., Teal, L.R., Somerfield, P.J., Austen, M.C., Barange, M., Sell, A.F., Allen, I., Peck, M.A., 2016.

Solutions for ecosystem-level protection of ocean systems under climate change. Global Change Biology 22, 3927–3936.

R Core Team, 2018. R: a language and environment for statistical computing. R Foundation for Statistical Computing, Vienna, Austria.

Redmond, M.D., Cobb, N.S., Miller, M.E., Barger, N.N., 2013. Long-term effects of chaining treatments on vegetation structure in piñon–juniper woodlands of the Colorado Plateau. Forest Ecology and Management 305, 120–128.

Reeves, M.C., Bagne, K.E., Tanaka, J., 2017. Potential climate change impacts on four biophysical indicators of cattle production from Western US rangelands. Rangeland Ecology & Management 70, 529–539.

Rehfeldt, G.E., Crookston, N.L., Sáenz-Romero, C., Campbell, E.M., 2012. North American vegetation model for land-use planning in a changing climate: a solution to large classification problems. Ecological Applications 22, 119–141.

Renwick, K.M., Curtis, C., Kleinhesselink, A.R., Schlaepfer, D., Bradley, B.A., Aldridge, C.L., Poulter, B., Adler, P.B., 2018. Multi-model comparison highlights consistency in predicted effect of warming on a semi-arid shrub. Global Change Biology 24, 424–438.

Robinson, D., Beukema, S., and Greig, L. 2008. Vegetation models and climate change. Available at: https://doi.org/10.13140/2.1.2485.6327, Accessed May 17, 2019.

Schlaepfer, D.R., Lauenroth, W.K., Bradford, J.B., 2012. Effects of ecohydrological variables on current and future ranges, local suitability patterns, and model accuracy in big sagebrush. Ecography 35, 374–384.

Simpson, E.H., 1949. Measurement of diversity. Nature 163, 688 –688.

Smith, M.R., 2017. Ternary: An R Package for Creating Ternary Plots. Zenodo.

Snyder, K.A., Evers, L., Chambers, J.C., Dunham, J., Bradford, J.B., Loik, M.E., 2019. Effects of changing climate on the hydrological cycle in cold desert ecosystems of the Great Basin and Columbia Plateau. Rangeland Ecology & Management 72, 1–12.

Still, S.M., Richardson, B.A., 2015. Projections of contemporary and future climate niche for Wyoming Big Sagebrush (*Artemisia tridentata* subsp. wyomingensis): a guide for restoration. Natural Areas Journal 35, 30–44.

Urban, M.C., 2015. Accelerating extinction risk from climate change. Science 348, 571–573.

US EPA, O., 2015. Level III and IV Ecoregions of the Continental United States. US EPA Available at https://www.epa.gov/eco-research/level-iii-and-iv-ecoregions-continental-united-states.

US Geological Survey. 2017. Federal lands of the United States. Available at: https://nationalmap.gov/small_scale/mld/fedlanp.html. Accessed 12 September, 2019.

van Mantgem, P.J., Stephenson, N.L., Byrne, J.C., Daniels, L.D., Franklin, J.F., Fule, P.Z., Harmon, M.E., Larson, A.J., Smith, J.M., Taylor, A.H., Veblen, T.T., 2009. Widespread increase of tree mortality rates in the western United States. Science 323, 521–524.

Weisberg, P.J., Lingua, E., Pillai, R.B., 2007. Spatial patterns of pinyon–juniper woodland expansion in central Nevada. Rangeland Ecology & Management/Journal of Range Management Archives 60, 115–124.

Yapp, G., Walker, J., Thackway, R., 2010. Linking vegetation type and condition to ecosystem goods and services. Ecological Complexity 7, 292–301.

Yates, K.L., Bouchet, P.J., Caley, M.J., Mengersen, K., Randin, C.F., Parnell, S., Fielding, A.H., Bamford, A.J., Ban, S., Barbosa, A.M., Dormann, C.F., Elith, J., Embling, C.B., Ervin, G.N., Fisher, R., Gould, S., Graf, R.F., Gregr, E.J., Halpin, P.N., Heikkinen, R.K., Heinänen, S., Jones, A.R., Krishnakumar, P.K., Lauria, V., Lozano-Montes, H., Mannocci, L., Mellin, C., Mesgaran, M.B., Moreno-Amat, E., Mormede, S., Novaczek, E., Oppel, S., Ortuño Crespo, G., Peterson, A.T., Rapacciuolo, G., Roberts, J.J., Ross, R.E., Scales, K.L., Schoeman, D., Snelgrove, P., Sundblad, G., Thuiller, W., Torres, L.G., Verbruggen, H., Wang, L., Wenger, S., Whittingham, M.J., Zharikov, Y., Zurell, D., Sequeira, A.M.M., 2018. Outstanding challenges in the transferability of ecological models. Trends in Ecology & Evolution 33, 790–802.

Zelikova, T.J., Hufbauer, R.A., Reed, S.C., Wertin, T., Fettig, C., Belnap, J., 2013. Eco-evolutionary responses of *Bromus tectorum* to climate change: implications for biological invasions. Ecology and Evolution 3, 1374–1387.

Zimmer, S., Grosklos, G., Belmont, P., Adler, P., 2020. Agreement and uncertainty among climate change impact models: a synthesis of sagebrush steppe vegetation predictions. 10.4211/hs.e6b15828d20843eab4e2babd89787f41. Accessed June 19, 2020.

Ziska, L.H., Reeves, J.B., Blank, B., 2005. The impact of recent increases in atmospheric CO_2 on biomass production and vegetative retention of cheatgrass *(Bromus tectorum):* implications for fire disturbance. Global Change Biology 11, 1325–1332.