

## The impact of climate change uncertainty on California's vegetation and adaptation management

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**Abstract.** The impacts of different emission levels and climate change conditions to landscape-scale natural vegetation could have large repercussions for ecosystem services and environmental health. We forecast the risk-reduction benefits to natural landscapes of lowering business-as-usual greenhouse gas emissions by comparing the extent and spatial patterns of climate exposure to dominant vegetation under current emissions trajectories (Representative Concentration Pathway, RCP8.5) and envisioned Paris Accord target emissions (RCP4.5). This comparison allows us to assess the ecosystem value of reaching targets to keep global temperature warming under 2°C. Using 350,719 km<sup>2</sup> of natural lands in California, USA, and the mapped extents of 30 vegetation types, we identify each type's current bioclimatic envelope by the frequency with which it occupies current climate conditions. We then map the trajectory of each pixel's climate under the four climate futures to quantify areas expected to fall within, become marginal to (outside a 95% probability contour), or move beyond their current climate conditions by the end of the 21st century. In California, these four future climates represent temperature increases of 1.9–4.5°C and a –24.8 to +22.9% change in annual precipitation by 2100. From 158,481 to 196,493 km<sup>2</sup> (45–56%) of California's natural vegetation is predicted to become highly climatically stressed under current emission levels (RCP8.5) under the drier and wetter global climate models, respectively. Vegetation in three California ecoregions critical to human welfare, southwestern CA, the Great Valley, and the Sierra Nevada Mountains, becomes >50% impacted, including 68% of the lands around Los Angeles and San Diego. However, reducing emissions to RCP4.5 levels reduces statewide climate exposure risk by 86,382–99,726 km<sup>2</sup>. These projections are conservative baseline estimates because they do not account for amplified drought-related mortality, fires, and beetle outbreaks that have been observed during the current five-year drought. However, these results point to the landscape benefits of emission reductions.

**Key words:** California vegetation; climate change exposure; ecological forecast; natural resource management; policy implications; risk assessment; watershed planning.

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## INTRODUCTION

The intensity of projected changes in climate, as represented by emission levels and changes in temperature and moisture, is increasingly important in strategic landscape planning. The impacts of future emissions to natural lands also have implications for ecosystem services, biodiversity conservation, and potentially ecosystem function (Hayhoe et al. 2004, Mazziotta et al. 2015). The degree to which these risks can be successfully relayed to policy makers can help them to understand the urgency of creating and meeting reduced emissions via policy.

Lands managed for natural attributes such as ecosystem services, biodiversity, or dominant vegetation require strategic selection of climate adaptation management practices (Rannow et al. 2014). Strategic management decisions relate to whether to maintain historical species, land-cover types, ecosystem processes, and resources; or to embrace and foster changes predicted by changing climates (Millar and Stephenson 2015). These decisions carry risk. Managing for current attributes and enhancing resilience to changing climate may be wasted effort if climate change and secondary effects such as increasing wildfire (Miller and Safford 2012) overwhelm the capacity of systems to be resilient. In contrast, managing for vegetation change could place species at risk if future climate projections used to set management objectives turn out to be inaccurate, and thereby encourage transition strategies that do not fit the new climate (Swanston et al. 2016).

Tools that natural resource managers can use to estimate the effects and severity of climate change on vegetation include movement-related metrics such as climate velocity (Loarie et al. 2009, Ackerly et al. 2010), dynamic global vegetation models (DGVMs; Gonzalez et al. 2010), or species distribution models (SDMs; Elith and Leathwick 2009). Climate velocity measures where current climate conditions from one location will be found at other locations in the future; the farther away conditions move within a set time, the greater the velocity, while lower velocity may occur in topographically heterogeneous regions (Loarie et al. 2009). Climate velocity has been used recently to identify the lag between the rate of tree range expansion and the rate-changing climate conditions (Sittaro et al. 2017). Species

distribution models have been widely used in climate change studies and are essentially a biological analog to climate velocity. They predict where future suitable climatic conditions for a species may be found, given correlative relationships of current climate to known current locations (e.g., Thorne et al. 2013). Dynamic global vegetation models are similar to SDMs but simulate spatial shifts in vegetation and may incorporate interactions between vegetation types and the environment. They can be run at various spatial scales including global (Gonzalez et al. 2010) or regional (Halofsky et al. 2013).

There are significant uncertainties, however, in biological parameters used to forecast biogeographic shifts under climate change (Dormann 2007). These include estimates of species' dispersal ability, establishment potential, sensitivity, and adaptive capacity to climate change, and competitive interactions (Summers et al. 2012, Renton et al. 2013), as well as their evolutionary history and habitat specificity (Williams et al. 2009). These areas of uncertainty may erode the predictive capacity of species response models (Hulme 2005) and limit proactive landscape adaptation actions. Additionally, the actual rate of climate change is uncertain. Although there is general agreement among global climate model projections for increasing temperatures, disagreement on precipitation levels (Hawkins and Sutton 2011) and uncertainty about future emission levels (Johns et al. 2003) are other factors that resource managers must consider.

This uncertainty suggests the need for additional approaches, particularly for place-based, or in situ, analyses that can be used to spatially stratify management and monitoring actions across the extent of a natural resource. Here, we develop such an analysis to provide a stratification of risk levels within an existing domain, the current extent of natural vegetation types in California, USA. This study examines how different sources of uncertainty in climate change (different emission scenarios, different climatological outcomes of climate models) affect the landscape of future vegetation in California. We frame the analyses both in the context of why mitigation efforts are important to managers grappling with adaptation (better control or governance of emissions reduces management uncertainty), and why adaptation efforts are important when developing mitigation policy

(successful greenhouse gas reduction will make adaptation more successful and less necessary).

We model the potential climate impacts to the natural vegetation of California, an area comprising 350,719 km<sup>2</sup>. Our approach takes advantage of increasingly detailed land-cover maps available for large regions, increasingly higher spatial resolution of projected changes in climate, and the Basin Characterization Model (BCM; Flint et al. 2013) that balances the hydrological budget with climate on a per-grid-cell basis across large areas. We summarize the spatial extent of in situ climate exposure for each vegetation type under four climate models and quantify the risk of remaining on the current business-as-usual emissions track of RCP8.5 in comparison with lowered emission levels thought to retain global temperature increases to about two degrees C, represented by the RCP4.5. We compare the extent and impact patterns to each vegetation type across the state and within the state's 10 major ecoregions. We highlight differences in vegetation stress under these models as they define two important aspects of uncertainty for adaptation management of natural vegetation: (1) uncertainty over achieving emissions reductions envisioned in recent global climate accords, and (2) uncertainty in the directionality of changes in available water projected by different global climate models (GCMs).

The approach is highly relevant for natural resource managers, who are constrained to their spatial jurisdiction and who need further detail on the varying levels of climatic stress that may be exerted on their lands. Such managers can glean information from models that portray movement, but ultimately these only partially inform spatial decisions about where to invest limited resources for climate adaptation. For example, although climate conditions currently in a park may shift 100s of kilometers (Dobrowski and Parks 2016), the resource managers at that location are responsible for those lands whatever the climate may become, and are therefore keenly interested in the climate risk, or exposure, that may occur on their lands. This leads to a fundamentally different perspective on what information is useful for supporting management decisions among land-based resource managers. Climate exposure information can also serve as a valuable input to broader scale conservation planning efforts that cross jurisdictional boundaries.

Natural resource agencies, conservation organizations, and others frequently work together to identify landscape-scale conservation priorities, develop conservation plans, implement restoration activities; incorporating spatial patterns of climate-induced vegetation stress can help to ensure that climate risks are addressed. The results from this study are currently in use by several groups in California (Appendix S1) for watershed- and regional-scale efforts.

## MATERIALS AND METHODS

We define climate exposure as the level of change in climate conditions expected in every pixel that a vegetation type currently occupies. The climate exposure analysis is calculated using the mapped extent of each macrogroup vegetation type. Every grid cell of each macrogroup is ranked according to how often that climate occurs in current time, relative to the entire area occupied by that macrogroup. The current time classification of a type's climate envelope is then used to track the transition of every grid cell under future projections. This allows a measure of the potential vegetation stress, or climate exposure, for all grid cells occupied by each vegetation type.

### *Vegetation data*

A 2015 statewide 30-m resolution vegetation map (California State Department of Forestry and Fire Protection GIS Data 2016; hereafter called the FRAP map) was used to determine the distribution of 30 macrogroup vegetation types (see Appendices S1 and S2: Fig. S1 and Table S1). The FRAP map can be portrayed by Macrogroups, the fourth level of generalization up from the most detailed vegetation descriptions (Associations) in the USA's National Vegetation Classification Standard (Federal Geographic Data Committee 2008). Macrogroups were used because these vegetation types also serve as terrestrial conservation targets in the 2015 California State Wildlife Action Plan, which serves as a vision for fish and wildlife conservation efforts in California (California Department of Fish and Wildlife 2015).

We analyzed 30 vegetation macrogroups (Appendix S1: Table S1), excluding Temperate Pacific Intertidal Shore (MG106) due to highly limited distribution. The vegetation map was resampled to a 270-m grid before analysis to align the

patterns of vegetation distribution with scale of the climate and hydrologic data used, resulting in vegetation data map comprising approximately 4.8 million pixels. We resampled the 30-m grid cells using majority sampling (ESRI 2015), which assigns the vegetation type occupying the most area within each new grid cell as the vegetation type for that cell.

### Climate data

We selected two future climate models from among 12 GCMs (Appendix S2), the MIROC ESM (Watanabe et al. 2011) and CNRM CM5 (Voltaire et al. 2013) and two emission scenarios (the RCP4.5 and RCP8.5; IPCC 2013) to compare change from current conditions in 1981–2010 with the 2070–2099 time period. These four climate futures all show warming for California and bracket future conditions by +1.9–4.5°C and –24.8 to +22.9% annual precipitation change from current conditions (Thorne et al. 2016). The use of a bracketing approach makes explicit the climatic conditions that are bounded within the study, and should climate change go beyond these bounds, the projections here would need to be rerun.

We used nine downscaled climate condition variables including mean annual minimum temperature ( $T_{\min}$ ), mean annual maximum temperature ( $T_{\max}$ ), and total annual precipitation (PPT; Flint and Flint 2012) at a grid resolution of 270 m, and six hydrologic variables derived from the BCM (Appendix S2: Fig. S2; Flint et al. 2013, Thorne et al. 2015), which balances the hydrologic budget on a per-grid-cell basis and produces a number of metrics of interest in ecological

modeling including those used here: potential evapotranspiration (PET), actual evapotranspiration, climatic water deficit (CWD), runoff (RUN), recharge (RCH), and snowpack (PCK; Table 1). These values were derived by adding or taking the mean of monthly time-step intervals for months comprising the water year in California (October–September) and then averaged for 1981–2010, downscaled from the 800 m the Prism climate surface data (California Department of Fish and Wildlife 2015, PRISM Climate Group 2014); and 2010–2039, 2040–2069, and 2070–2099, derived from the two GCMs and emission scenarios.

### Climate exposure analysis

An overarching vegetation climate exposure model was implemented in R (version 3.1.2), using the vegetation, climate, and hydrology raster files as the primary input data. The climate condition files were randomly sampled at 100,000 points across California to fit a statistical model characterizing the relationship between climatic variables both in the current time and for the modeled future data.

At each of the 100,000 points, the nine climate condition variables (Table 1) for the current time period and in three future time periods were used to characterize the range and variation of conditions in the study region. We conducted this exercise for each of the four GCM/emission scenarios tested, separately. The variables were modeled using a principal components analysis to identify the dominant components of variation. The top-two principal components axes, representing a mean of 79.3% of the variability across the four

Table 1. Nine climate and hydrology variables used to model bioclimatic envelopes for California vegetation types.

Variable	Units	Description
Maximum temperature ( $T_{\max}$ )	°C	Maximum monthly air temperature averaged annually
Minimum temperature ( $T_{\min}$ )	°C	Minimum monthly air temperature averaged annually
Precipitation (PPT)	mm	Total monthly precipitation (rain or snow) summed annually
Potential Evapotranspiration (PET)	mm	Total amount of water that can potentially evaporate from the ground surface or be transpired by plants summed annually
Runoff (RUN)	mm	Amount of water that becomes stream flow, summed annually
Recharge (RCH)	mm	Amount of water that penetrates below the root zone, summed annually
Climatic water deficit (CWD)	mm	Annual evaporative demand that exceeds available water, summed annually
Actual evapotranspiration (AET)	mm	Amount of water that evaporates from the surface and is transpired by plants, limited to available soil water, summed annually
Snowpack (PCK)	mm	Amount of snow that accumulated per month summed annually for April 1st

climate projections, were extracted as a two-dimensional space (Appendix S1: Table S2). This was done to simplify the representation of the hydroclimate space, while maintaining the most important information on the variables to be associated with the observed vegetation distributions. Dominant factor loadings for the first principal component relate to heat and drought attributes and explain a mean of 64.8% of the variation, represented by CWD, PET, and mean annual maximum temperature ( $T_{max}$ ) for MIROC ESM and by CWD, PET, and annual precipitation (PPT) for CNRM CM5. The second principal component, explaining a mean of 14.3% of the variation, is dominated by cool and moisture attributes with mean annual minimum temperature ( $T_{min}$ ), PPT,

RCH for MIROC ESM, and by  $T_{min}$ , PPT, and RUN for CNRM CM5 having the dominant factor loadings (Appendix S1: Table S3).

#### Vegetation group climate exposures

Macrogroup climatic envelopes were identified using a two-dimensional kernel density estimator on the first two principal components of current climate conditions on all observations for each macrogroup (Inset Fig. 1A). The result is a smoothed continuous point density surface, showing the prevalence of each vegetation type across the range of two-dimensional climate conditions. This surface was partitioned by fitting contour lines so that they enclose a proportion of the original points from the current time period.

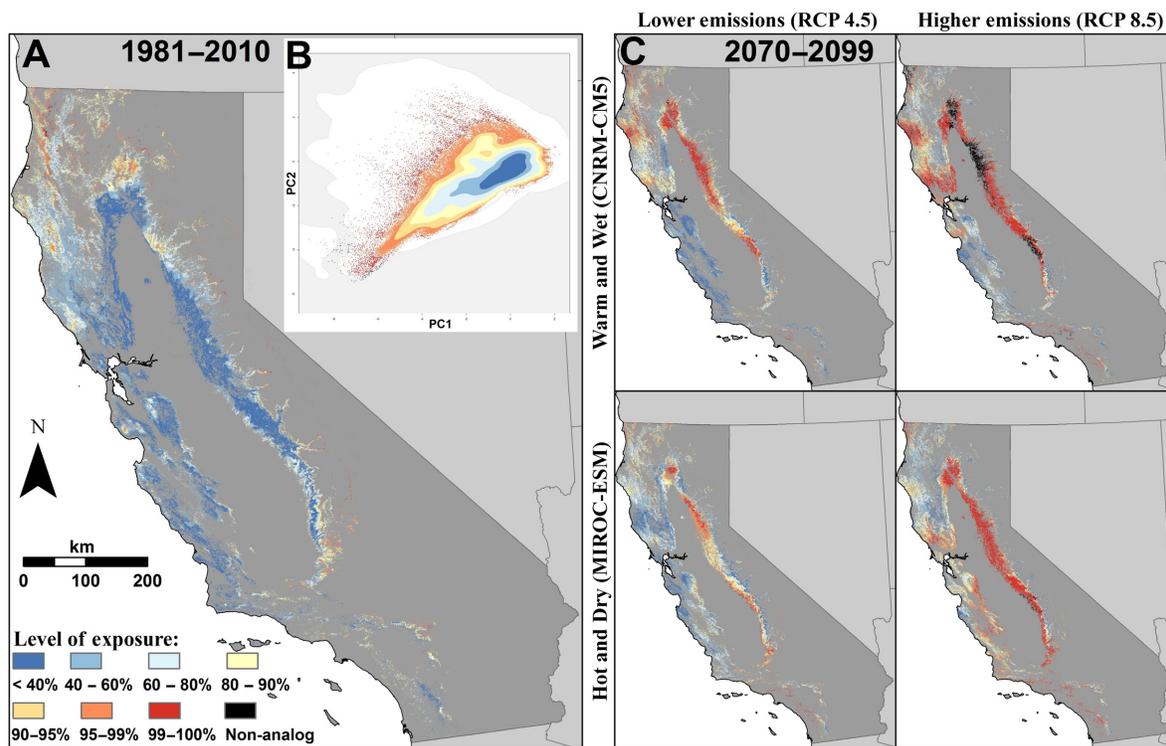


Fig. 1. An example of the classification of the current extent of a vegetation type by commonness of its current climate conditions. (A) The 2015 mapped extent of California Foothill and Valley Forests and Woodlands (MG009), classed into varying levels of current climate suitability. Locations in the <80% categories (three shades of blue) are those where it most commonly occurs and therefore is thought to be the least stressed. Vegetation at locations in the 95–99% (orange) and higher (red) classes is area that is already on the climatic margins of where the type occurs. The inset (B) represents the distribution of the vegetation when the current climate conditions are reduced to two dimensions using a principal components analysis. Colors in the inset and the map refer to the same categories of exposure to climate conditions. (C) The climate exposure of the same vegetation type by end-of-century under the four futures.

Contours were calculated at 5% increments, with the innermost 5% contour line enclosing the 5% of a selected vegetation type's pixels that are at the core of the climate space for that type, as determined by its density in the climate space. Cells farther away from the dense central core are considered to be more marginal in that vegetation type's distribution. The outer contours are fit to enclose the 95–99% of climatically marginal points, with the last 1% of cells (beyond the 99% contour) being the most marginal. For several vegetation types, there are a few extreme points that are far outside the general distribution for the type. These outlying points may be due to data processing errors, misclassification of vegetation, microclimatic conditions not captured by the climate data, or chance events.

In the initial 1981–2010 time period (current time), pixels by definition follow a uniform distribution across the frequency kernel classes. Climate conditions that a vegetation type currently occupies 80% of the time are considered suitable and not stressful for that type, while the areas containing 80–95% climate conditions are termed neutral, with no assumption about an associated degree of stress. We define currently marginal climate conditions as those occurring in only five percent of the areas occupied by each vegetation type.

Once each vegetation type's current climate envelope is defined (e.g., Fig. 1A), we assess the relative impact of future climate projections by tracking the climate change in each type's pixels (e.g., Fig. 1B). Future climate exposure is calculated using the same principal components values in each pixel for each vegetation type in three future time periods (2010–2039, 2040–2069, and 2070–2099). Mean climatic conditions at each location for each time were calculated as the average of the constituent individual years. Future conditions for each pixel were then mapped with respect to where they fell on the current climate frequency contours of their vegetation type. We defined vegetation type pixels whose future climates fall outside their current 95% contour as climatically exposed, and outside the current 99% contour for their vegetation type are considered highly exposed to climate change. In addition, if a future cell's climate condition is outside the current climate 99% contour of all vegetation types in California, it was considered to be non-analog; that is, its future climate

conditions are not ranked in the climates currently sampled (1981–2010). We consider these points to be highly exposed. We consider points that fall within 80% of the current climate conditions under future projections to have low or no stress, because the vegetation type currently experiences these conditions in many locations.

We summarize the impacts of climate change on California's natural vegetation for 10 ecoregions in the state and in terms of which vegetation types appear most climatically exposed, presenting the results for the end-of-century time period.

## RESULTS

Of the 350,719 km<sup>2</sup> of California's natural vegetation in current time, 17,536 km<sup>2</sup> (5%) is by definition climatically marginal, derived by identifying the locations of the 5% least frequently occupied climate conditions for each vegetation macrogroup. Under the RCP8.5 business-as-usual rate of anthropogenic emissions, an additional 140,945 km<sup>2</sup> (40% of California's natural lands) becomes climatically marginal under the MIROC ESM model by 2100. The number is similar for the wetter GCM tested, CNRM CM5 RCP8.5, which produces an additional 178,957 km<sup>2</sup> of climatically marginal natural vegetation (51% of CA's natural lands) by end-of-century. If global emissions could be reduced to the RCP4.5 level, the corresponding additional exposure is 54,563 km<sup>2</sup> under MIROC ESM (16% of CA natural vegetation) and 79,231 km<sup>2</sup> under the CNRM models (23%; Table 2; Fig. 2). The climatically non-analog component of these results by end-of-century is <1% of all natural vegetation under both RCP4.5 scenarios, but 7.4% under the MIROC ESM and 11.6% under the CNRM CM5 RCP8.5 scenarios. The difference between RCP4.5 and RCP8.5 scenarios ranges from 86,382 to 99,726 km<sup>2</sup> of vegetation projected as stressed by the end-of-century; an area approximately the size of Portugal.

The vegetation of six of California's ten ecoregions (Hickman 1993) is over 50% climatically marginal by end-of-century under the wetter RCP8.5 GCM, and four of those ecoregions also reach this level of impact under the drier RCP8.5 GCM (Appendix S1: Table S4), further described here: Central Western California's vegetation has the least impacts, with 16% and 19% climatically exposed by end-of-century under the CNRM

Table 2. The area under marginal climate using a 5% threshold and the area retained as suitable under the 80% values for the four climate futures.

Total natural lands (350,719 km <sup>2</sup> )	Current time (1981–2010)				
	Area (km <sup>2</sup> )	Value (%)	Area (km <sup>2</sup> )	Threshold (%)	
	280,575	80	17,536	5	
		Not stressed (<80%)	Stressed (>95%)		
CNRM 4.5	2010–2039	50,106	14	43,082	12
	2040–2069	68,691	20	57,688	16
	2070–2099	112,091	32	96,767	28
CNRM 8.5	2010–2039	59,375	17	47,347	14
	2040–2069	92,878	26	82,982	24
	2070–2099	188,021	54	196,493	56
MIROC 4.5	2010–2039	14,400	4	26,830	8
	2040–2069	43,521	12	47,703	14
	2070–2099	77,028	22	72,099	21
MIROC 8.5	2010–2039	10,219	3	24,902	7
	2040–2069	73,148	21	67,840	19
	2070–2099	157,931	45	158,481	45

CM5 and MIROC ESM, respectively; and the Sierra Nevada, particularly important for ecosystem services, is 31% and 25% climatically exposed under RCP4.5, but 55% and 62% under the RCP8.5 scenarios for CNRM and MIROC, respectively. The southwestern coast ecoregion containing Los Angeles and San Diego will experience 63–69% climatically exposed vegetation under CNRM and MIROC ESM RCP8.5 by end-of-century. Climatically non-analog conditions emerge along the lower elevations of the western Sierra Nevada under the wetter GCM; and the Sonoran Desert has the most end-of-century extent of non-analog climate conditions (65% and 72% of the ecoregion under RCP8.5 MIROC ESM and CNRM CM5, respectively) with hotter conditions that are typically found across the border in Mexico developing in the southern part of California. It also contains the highest proportion of climatically exposed vegetation among the ecoregions.

Vegetation in the state's northern three ecoregions (Modoc Plateau, Cascade Ranges, and northwestern) experiences relatively fewer impacts than the ones in the south. The wetter future also produces more climatically marginal conditions than the drier one, and the two model runs using the RCP8.5 scenario cause considerably more impacts than those using the RCP4.5 scenario (Appendix S1: Table S5).

Of the 30 vegetation macrogroups, 23 cover more than 1000 km<sup>2</sup>, 16 and 12 of whose extents

are over 50% climatically exposed by the end-of-century under CNRM CM5 and MIROC ESM RCP8.5 scenarios, respectively, while only five and two have that level of impact under the RCP4.5 scenario (Appendix S1: Table S5).

Under both RCP8.5 scenarios, 43% of California's aggregate forest and woodland types are climatically marginal by the end-of-century, whereas under the RCP4.5 scenarios these types are 16.5–22.7% climatically marginal (Appendix S1: Table S5). Warm Southwest Riparian Forest is the most impacted among the California vegetation types that currently occupy >1000 km<sup>2</sup>. Intermountain Basins Pinyon-Juniper Woodland, Vancouverian Rainforest, Rocky Mountain Subalpine, and High Montane Conifer Forest, and California Forest and Woodland are all more than 50% climatically exposed under CNRM RCP8.5. The drier MIROC RCP8.5 finds the Rocky Mountain Subalpine and High Montane Conifer Forest, Vancouverian Rainforest, and California Forest and Woodland the most exposed after the Warm Southwest Riparian Forests.

For shrub-dominated vegetation types over 1000 km<sup>2</sup> in extent, Great Basin Upland Scrub and Great Basin Dwarf Sagebrush Scrub are both over 90% exposed under the RCP8.5 scenarios, and all the more xeric shrub types are over 70% exposed under CNRM RCP8.5. Coastal Sage Scrub is 59–62% exposed under the RCP8.5 scenarios, while the extensive Chaparral Type is

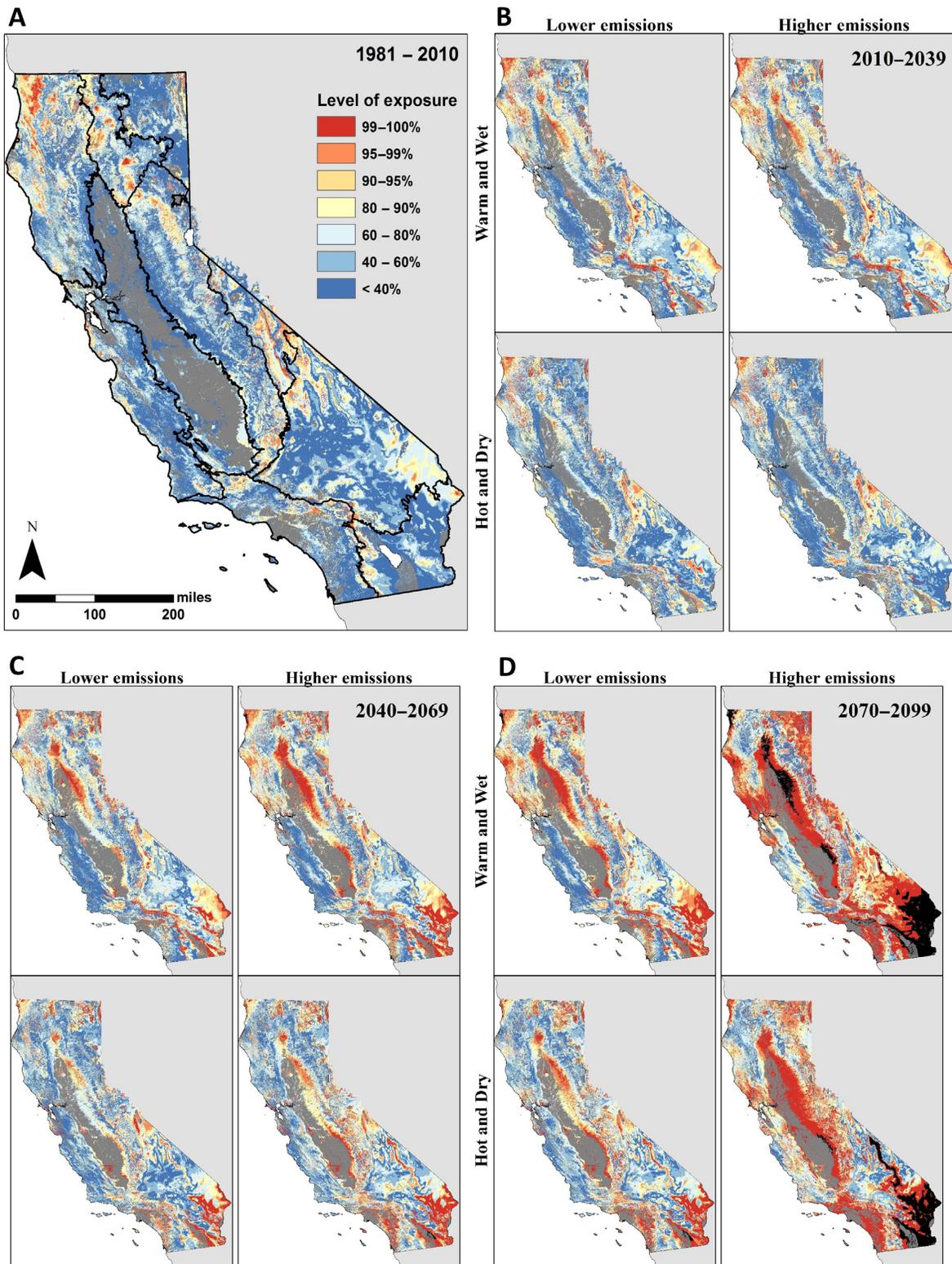


Fig. 2. Mapped climate exposure under four climate projections. This image shows the climate exposure of 30

(Fig. 2. *Continued*)

California macrogroups under the four climate projections for current time (A) and three time future periods: (B) 2011–2039, (C) 2040–2069, and (D) 2070–2099. Areas considered to be highly climatically exposed are in the 95–99%, 99–100%, and non-Analog categories. Areas with values <80% are considered to be in climatically suitable conditions for the vegetation that currently occupies them. “Warm and Wet” = CNRM CM5, “Hot and Dry” = MIROC ESM, Lower Emissions = RCP4.5, and Higher Emissions = RCP8.5. Gray areas are urban and agricultural, which were not evaluated.

between 38% and 42% exposed under the RCP8.5 scenario. California’s grasslands are 26–29% more exposed under the RCP8.5 than under RCP4.5.

## DISCUSSION

We found that reducing global greenhouse gas emissions has the potential to greatly reduce the negative effects of climate change on California’s natural vegetation, as well as to lower uncertainty regarding adaptation management. These results have application therefore to both policy and resource management. We found that climate risk to California’s current vegetation is 2–2.2 times higher if emissions remain on the RCP8.5 emissions track than if society is able to reduce emissions to the RCP4.5 track that would keep warming to approximately 2°C globally (IPCC 2013, Karmalkar and Bradley 2017). Further, model results across GCMs are more variable under the current RCP8.5 emissions than under a reduced emission trajectory. These observations have important ramifications with respect to both California’s climate legislation (CA AB32 2013, CA SB375 2016) and global agreements (e.g., The Paris Agreement ratified in 2015 at the United Nations Framework Convention on Climate Change, United Nations 2015). Achieving Paris Agreement goals would likely result in future climate that is much closer to the RCP4.5 projections than the RCP8.5 projections, which would substantially reduce climate risk to California vegetation types and decrease management uncertainty.

By contrast, the difference for California’s vegetation climate exposure is less strongly driven by the GCMs that portray future climate than by the emission levels. There is a difference of 38,012 km<sup>2</sup> (~20%) in the extent of highly climatically exposed natural vegetation at the end of the 21st century between the wetter and drier RCP8.5 GCMs under the RCP8.5 emissions scenario, but the area maintained out of the climatically

marginal category with emissions tracking the RCP4.5 scenario rather than the RCP8.5 is 50.8% for the CNRM CM5 and 54.5% for the MIROC ESM.

Some ecoregions and vegetation types are inherently more at risk than others. We assumed that if more than 50% of an ecoregion becomes climatically stressed, it enters a higher level of risk overall. By this measure, six of the 10 ecoregions are at high risk by end-of-century under CNRM CM5 RCP8.5, and four of those are also selected by the MIROC ESM RCP8.5 model (Appendix S1: Table S4). Selection by both the wetter and drier models leads to several concerns for these four ecoregions. First, in southwestern CA, urban expansion is a major factor for loss of natural vegetation (Thorne et al. 2017). Increased climate stress in this region may lead to intensified interactions between dynamics such as fire in remaining natural vegetation, and increased population pressure.

Second, in the Sierra Nevada, high levels of stress indicated for the lower and mid-elevations could have major consequences with regards to vegetation conversion and associated potential impacts to ecosystem services such as water delivery (Thorne et al. 2015). In addition, intensified climate stress will increase the risk of wild-fire and drive it to higher elevations than historically (Schwartz et al. 2015, Liang et al. 2017). Third, high levels of climate exposure to natural vegetation in California’s Great Valley may also impact agricultural production (Thorne et al. 2017).

However, a vegetation type we identify as climatically exposed by end-of-century may not be, if that vegetation extends beyond our study area border. This may be applicable for the Sonoran Desert, the fourth ecoregion selected by both RCP8.5 models as high risk, and containing significant future extents of non-analog conditions. The Sonoran Desert extends south into Mexico,

and future climate conditions we modeled would likely be considered less extreme if the Sonoran Desert's full extent were sampled. This may mean that this vegetation has ability to withstand greater temperatures, because it is already found in hotter places.

Methods for assessing plant species or vegetation type climate vulnerability include purely spatial approaches (Choe et al. 2017), approaches that include only plant functional types or the biological attributes of sensitivity and adaptive capacity (Foden and Young 2016), and approaches that include indirect effects of landscape condition such as landscape fragmentation as a part of the scoring (Comer et al. 2012). In many cases, predictions of how individual species will respond to climate change rely in part on expert opinion and published literature. If this approach were applied here, it would need to link dominant species of each vegetation type to the vegetation types used. Given differential exposure to climate conditions, attributes of the biology of systems and their disturbance regimes will likely strongly impact the ability of resource management to direct outcomes. The sensitivity and adaptive capacity of component dominant plant species could make some vegetation types more or less vulnerable to modeled climate change. Because knowledge about each vegetation type and associated species' physiological responses to climate varies, an overall rollup to a vulnerability class includes assumptions that introduce additional uncertainty as well as a generalization of all component metrics for cross-comparative purposes. For these reasons, we restrict this publication to climate exposure scores for each vegetation type. We previously found that the dominant species' sensitivity and adaptive capacity in the vegetation types analyzed were at least an order of magnitude less important with regard to their climate vulnerability than the emissions scenarios (Thorne et al. 2016).

While climate exposure projections can identify areas of a vegetation type's extent that become unsuitable, they can also identify the areas that retain climatic suitability, or climate change refugia (Figs. 1, 2). The integration of remote sensing-based data for landscape condition has found application in other fields, such as tracking the relative success of forest management policies to detect leakage of carbon via

deforestation (le Polain de Waroux et al. 2016) and compliance (Heilmayr and Lambin 2016). This study illustrates the utility of integrating land-cover maps derived from remote sensing with climate projections specifically to measure in situ risk, which has the advantage of avoiding many of the assumptions inherent in SDMs and DGVMs (Wiens et al. 2009).

In situ climate exposure projections are best used in concert with other knowledge of the landscape risks and of potential species interactions. Our scores are conservative estimates of climate risk due to a variety of compounding factors that affect vegetation, including extreme events such as multi-year droughts or short-duration heavy precipitation events, and secondary impacts such as large wildfires, insect outbreaks, and invasive species incursions. For example, phenomena associated with the recent five-year drought (2012–2016), which could be much more common under future climates (Cook et al. 2015), include an increase in tree mortality. Much of this tree mortality is caused by beetle outbreaks and pathogens (van Mantgem et al. 2009), promoted due to physiological stress in the trees indicated by increases in CWD (Asner et al. 2016, Young et al. 2017). The recent tree dieback of 100 million trees in California includes areas with high levels of tree mortality in the southern Sierra Nevada (Potter 2016, USDA Office of Communications 2016) that we predict will become stressed in the future under all of the future emissions and GCMs. This indicates that climate impacts, including the secondary effects of pathogens and disturbance regimes, may be advancing faster than our climate exposure projections, and increases our confidence in the predicted spatial patterns of vegetation stress. Further, the empirical observations suggest that forest ecosystem conversion is less likely to proceed through gradual stand replacement as a consequence of reduced recruitment success by dominant species (Chapin et al. 2004), and more through vegetation conversion events driven by disturbance may become more common in the future (e.g., Batllori et al. 2017).

Recognizing limitations of climate exposure metrics can help guide their use in resource planning. First, climatically marginal conditions are identified at both the wet and the dry ends of a vegetation type's distribution. This was particularly

evident for the widely distributed and ecologically important California Foothill and Valley Forests and Woodlands, which includes both broadleaf and conifer species (Fig. 1B). Under the wetter CNRM RCP8.5 future, some parts of its distribution in the central and northern Sierra Nevada become non-analog. These are areas that become warmer, but also wetter, and the degree of stress in this case is difficult to quantify. While these conditions might be cause for optimism that impacts to vegetation will not be as pronounced, we previously found that plant water stress, as measured by one of the predictors used here (CWD; Stephenson 1998), increases under these conditions, and evaporative demand due to warming temperatures outstrips the potential increase in soil moisture availability (Thorne et al. 2015). In this case, the additional uncertainty could be used to justify long-term monitoring or some experimentation, to determine the trajectory these woodlands may actually be on.

Second, while in situ measures can provide relative levels of expected stress, the actual physiological point at which different species comprising the vegetation types become highly stressed is still unknown. Our use of the least frequently occupied five percent threshold to describe climatically marginal conditions may not be the appropriate level. On the lower end, we left the 80–95% undefined as either stressful or not. We also quantified (Appendix S1: Tables S4 and S5) the 1% least frequently occupied, as well as non-analog conditions as other potential markers of climatic stress. Because the climate exposure analysis values are continuous, if other levels of exposure are identified as critical tipping points, those can be incorporated. Our climate exposure analysis also provides landscape explicit hypotheses about what areas are expected to be stressed or not. As time and climate change progress, tracking what actually happens to existing vegetation will provide the data to confirm or potentially adjust assumptions about critical climate exposure levels.

Finally, this approach does not predict where plant species that are the major components of each vegetation type may move to or whether vegetation types will disassemble. Models depicting movement could be used in conjunction with our portrayals of landscape condition. We might expect vegetation disassembly to occur in areas

projected with the greatest stress, while areas that a vegetation type is expected to remain within current suitable conditions could be areas that the component species do not migrate from. Such combinations of outcomes, if modeled from the same starting and for the same future conditions, could prove additionally informative, albeit with the limitations of both types of approaches kept in mind (see *Introduction* for limits on SDMs).

However, climate exposure analysis can inform climate adaptation management strategies because it can differentiate relative stress to existing vegetation, which has a high level of relevance for managers. By identifying regions where vegetation is projected to be climatically exposed early, and areas projected to be less climatically exposed throughout the 21st century, spatial stratification of where we expect existing vegetation to persist versus areas at high risk can be identified. Specifically, areas that are projected to be climate refugia may be locations where strategies to build resilience may be best achieved (Keppel et al. 2012, Morelli et al. 2016). Managing to increase the resilience of current vegetation types allows more time for species and communities to respond to climate through adaptation and dispersal. In contrast, locations projected to become highly exposed may be good candidates for ecosystem realignment to future climate states (Millar and Stephenson 2015).

## CONCLUSIONS

Natural resource managers must choose climate adaptation strategies in the face of large uncertainty and policy makers can help. Some fraction of this uncertainty arises from variation among climate models, imperfect understanding of vegetation responses to climate, and complex direct (physiological) and indirect vegetation responses that interact through physical disturbance (i.e., fire) as well as through biotic pathways (i.e., pests and pathogens). Uncertainty for managers is reduced if global agreements on carbon emission reductions could be achieved because reducing emissions reduces climatic forcing. Climatic forcing introduces the other uncertainties associated with ecological responses. Managing vegetation in the face of this uncertainty begins therefore with assessing the likelihood of achieving policy directives to reduce

emissions. The failure to achieve policy objectives (i.e., follow the RCP4.5 emissions pathway) in this study is that 24–28% more of California's natural lands are projected to become climatically marginal by remaining on the current emission trajectory. Climatically marginal environments can suffer massive mortality when subjected to drought stress (van Mantgem et al. 2009, Park Williams et al. 2013), as witnessed by enormous drought-related tree mortality during California's most recent drought. We show that emission reductions are vitally important for resource managers because they are likely to matter substantially in making adaptation strategies, particularly when choosing to actively realign vegetation types, or use natural disturbance events to change future management objectives (e.g., re-classifying site types in burned forests).

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