

Climate Change Vulnerability Assessment of Rare Plants in California



Project Report
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ABSTRACT

We assessed climate change vulnerability of 156 rare plant species of California. Our work can be divided into three complementary parts. First (1), we assigned a climate change vulnerability score to each of 156 rare plant species. The vulnerability scores are based on life history attributes and distribution model results, as specified by the Climate Change Vulnerability Index (CCVI) of NatureServe. The resulting CCVI scores were extremely vulnerable ($n = 2$), highly vulnerable ($n = 40$), moderately vulnerable ($n = 57$), presumed stable ($n = 32$), increase likely ($n = 16$), and insufficient evidence ($n = 9$). The most vulnerable species in our subset were *Piperia yadonii*, *Mimulus purpureus*, *Calliandra eriophylla*, *Limosella subulata*, and *Taraxacum californicum*. The species were scored as extremely vulnerable to highly vulnerable, based on their life history traits and geographic ranges. Second (2), we conducted a follow-up sensitivity analysis which showed that the distribution model results were highly dependent upon both model algorithm and model configuration. However, 60 of the 156 species were predicted to have declines in climatic suitability regardless of model algorithm and model configuration. Third (3), we calculated the topographic variability around known occurrences of each species ('topographic complexity'). The topographic complexity value of each species can be used to rank a group of species at a finer scale. For example, of the 40 species in the highly vulnerable CCVI score, some occur in relatively flat landscapes (low topographic diversity) and others occur in topographically dissected landscapes (high topographic diversity). It is possible that species that occur in topographically complex landscape will be less vulnerable to climate change because they can find suitable climates locally. We make recommendations for improving NatureServe's CCVI in general, and make specific recommendations for plants. Our results can be used to guide monitoring, management, and conservation plans for rare plant species.

INTRODUCTION

Climate change may negatively impact the flora of California, a biodiversity hotspot with over 2000 endemic plant species. Climate change may also reduce and extirpate populations (Pounds et al. 2006), cause species to migrate north and upslope (Parmesan 1996, Kelly and Goulden 2008, Loarie et al. 2008), advance flowering times, promote species invasion, increase disturbance (e.g. fire), and cause community reorganization (Walthier et al. 2002, Burkett et al. 2002). Several tools have been developed to identify which species and habitats are most imperiled by the negative impacts of climate change (Patwardhan et al. 2007, Williams et al. 2008, Heller and Zavaleta 2009, US EPA 2009, Glick et al. 2010, Byers et al. 2011, Schlesinger et al. 2011), under the assumption that the world will continue to warm in the near term, even if emissions are reduced (IPCC 2007). Most studies focus on how particular species or communities will respond to climate change, although a recent study used landscape-level spatial modeling to assess vulnerability using landscape indicators, such as 'climate stress', topographic diversity, and habitat fragmentation (Klausmeyer et al. 2011).

Species-level vulnerability assessments are typically based on intrinsic life history traits, species distribution models (SDMs), or both. The trait-based approach requires that a set of species attributes are identified and ranked according to their vulnerability to climate change. The sum of these scores represents the species' overall vulnerability to climate change and a list of species can then be ordered with regards to their predicted vulnerability. For example, the IUCN analyzed species life history, ecology, behavior, physiology, and genetic makeup of 'red list' species to assess vulnerability to climate change (Foden et al. 2008). SDMs are a second set of tools used to assess vulnerability to climate change (Pearson and Dawson 2003, Loarie et al. 2008, Stralberg et al. 2009). Typically, point occurrence data for a species are used to create a statistical model of climatic suitability using historical (often 30 year mean) climate. This model is then used to predict the species' contemporary range, based on a grid of historical climate, and the species' future range, based on a grid of predicted future climate. Finally, the change in range size and the amount of range overlap is calculated. Species with large

range reductions and/or low range overlap are considered to be more vulnerable than species with small range reductions and/or high range overlap. Climate-only SDMs suggest CA endemics may be in trouble: ‘66% will experience 80% reductions in range size within a century’ (Loarie et al. 2008). In addition, the velocity of predicted climate change outpaces the ability of most plants to adjust their ranges (Loarie et al. 2009).

A leading example of incorporating both species traits and SDMs comes from NatureServe, a non-profit organization whose mission is to provide the scientific basis for effective conservation action. NatureServe developed the Climate Change Vulnerability Index (CCVI) to serve as a standardized methodology to assess vulnerability to climate change at the species level. The CCVI consists of a Microsoft Excel document with four main sections: Section A - Direct exposure to climate change, specifically temperature and precipitation; Section B - Indirect exposure to climate change, including sea level rise, natural and human barriers, and land impacts from climate mitigation; Section C - Sensitivity factors, including plant life history attributes; and Section D - modeled response to climate change.

For this project, we assessed climate change vulnerability of 156 rare plant species in California. The California Native Plant Society (CNPS) Rare Plant program currently recognizes 1625 plant species as rare or endangered (27 California Rare Plant Rank 1A - presumed extinct in California; 1116 Rank 1B – rare or endangered in California or elsewhere; 482 Rank 2 – rare or endangered in California, but more common elsewhere) (<http://www.rareplants.cnps.org/>). While many of these are subspecies and varieties, and thus the words ‘taxa’ and ‘taxon’ are more appropriate than ‘species’, we use ‘species’ throughout for simplicity. Of the 1625 species, 932 (21 1A + 911 1B) are endemic to California. These 932 rare California endemics represent 42% of the 2260 species that are endemic to California (2260 is the total number of plant endemics, including unlisted and listed species). In other words, rarity is an important component of California’s botanical heritage. These rare species may have narrow ranges, small popu-

lation sizes, or narrow habitat preferences (or all of the above) due to natural or anthropogenic factors (www.cnps.org/cnps/rareplants/inventory). Importantly, perceived impacts of climate change was not a factor considered by CNPS when listing species as threatened or endangered. Thus, which of these 1625 species will be most vulnerable to climate change remains an uninvestigated question.

Our work can be divided into three complementary parts. First (1), for our subset of the 1625 rare plants ($n = 156$), we compiled a set of life history attributes and created distribution models as specified by the CCVI of NatureServe. Second (2), we conducted a sensitivity analysis to determine how variable range predictions were when model configuration and model algorithm were varied. Third (3), we calculated an index of vulnerability based on topographic variability around known occurrences (‘topographic complexity’).

METHODS

I. Climate Change Vulnerability Index (CCVI)

CCVI overview

Assessing vulnerability involves determining the severity and scope of the exposure that species experience, and combining this with species’ sensitivity and capacity to adapt to climate change (Fig. 1; Young et al. 2010). The CCVI examines how changed climate in a species range will impact a species using factors known to be associated with vulnerability to climate change, including species-specific factors as well as external stressors imposed by human actions. The CCVI

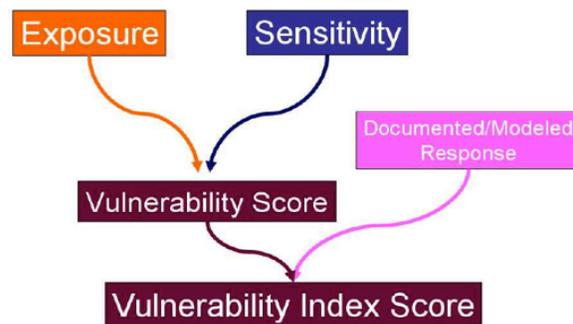


Fig. 1. Vulnerability assessment components (Taken from Young et al. 2011)

used a series of factors to assess climate change vulnerability; factors considered in evaluating response may be divided into four general categories (Fig. 1), including direct exposure, indirect exposure, sensitivity, and modeled response (see below). Detailed information including the scientific references used to develop each factor and the limitations of the methodology are given in Young et al. (2010) and Young et al. (in press).

Species selection

To create our list of focal species, we classified each species into one of the forms of rarity, described by Rabinowitz (1981). The forms of rarity come from intersecting range size (small or large), population size (small or large), and habitat specificity (habitat specialist or generalist). Only seven of the eight groups are 'rare' (i.e. large range, large population, habitat generalist is considered common). However, since the species with large ranges, large populations, and generalist habitat preferences for rare plants are still relatively rare with respect to the average species in the flora, we used all eight groups for our selection.

We used information from the California Natural Diversity Data Base (CNDDDB) to attribute each species with three variables required for rarity type classification:

- Range size: The sum area occupied, based on the polygons of the CNDDDB.
- Population size: the median population number of individuals, extracted from the comment field of CNDDDB.
- Habitat specificity: substrate affinity taken from the habitat field of CNDDDB.

For range size and population size, species were designated as large or small based on their value relative to the median of the distribution of values. We then selected an equal number of species from each of the eight rarity types. Our list of 156 species includes 139 California Rare Plant Rank 1Bs, 13 Rank 2s, and 3 Rank 3s.

CCVI data sources

CA-DFG, CNPS, and NatureServe have developed extensive information about the distribution, natural history, and conservation status of rare species and habitats. After consulting CNPS, NatureServe, CNDDDB, and available data in on-line databases, data gaps were identified and expert biologists and botanists were consulted to fill in the data gaps as needed for particular species. Collected data and sources for each species are included in a separate on-line (Appendix 2) profile sheet. The profiles contain cited literature and explanations for the vulnerability score.

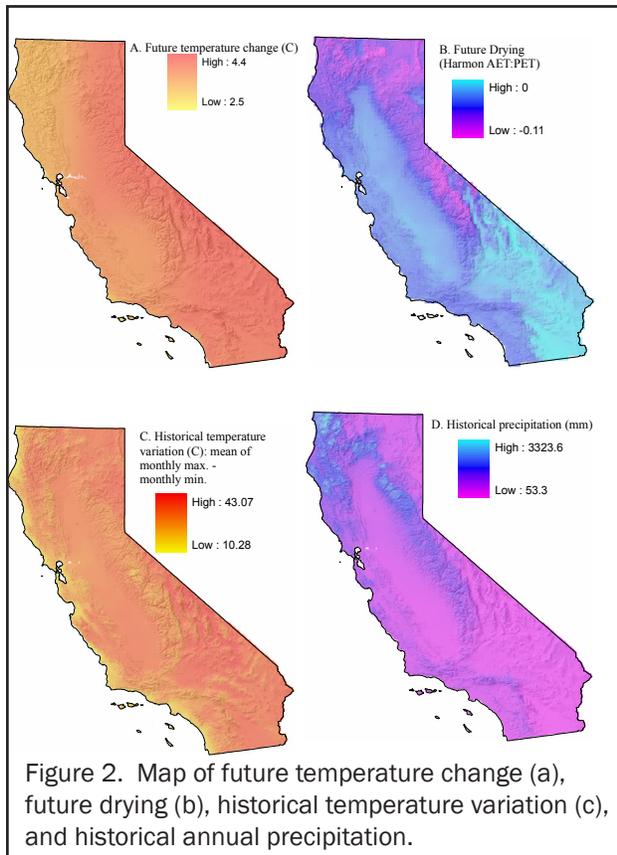
For use in analysis, we also determined the duration (USDA Plants Database), growth form (USDA, NRCS, 2011), and biogeographic affinity (Raven and Axelrod 1978) of each species, defined as follows: Duration - annual, perennial; Growth form - forb, graminoid, shrub, and tree; Biogeographic affinity - California Floristic Province, Madro Tertiary, North Temperate, and Warm Temperate Desert.

Northern affinity or Arcto-Tertiary clades are believed to come from the cooler and wetter portions of the mesic, pan-temperate Eocene flora; during subsequent aridification, these groups persisted in the more mesic regions and microclimates of the state. Southern affinity groups are believed to have developed in arid or semiarid ancestral climates; they include the Madro-Tertiary, warm temperate desert, and 'Californian' groups of Raven and Axelrod (1978), which became increasingly prominent in California from the Oligocene onward.

Climate data (Fig. 2a-d) for historic and for the year 2080 was downloaded from The Nature Conservancy's Climate Wizard (www.climatewizard.org), and displayed in a GIS.

CCVI Section A: Direct Exposure

Climate change exposure is divided into direct exposure (projected changes in temperature and moisture availability within the species' range) and indirect exposure (distribution relative to sea level rise, natural and anthropogenic barriers to dispersal, and new



land uses aiming to mitigate climate change).

Direct exposure is scored based on the percentage of the species' range within California that falls into categories of projected changes of temperature or moisture. Temperature change is the predicted change in annual temperature by 2080, calculated over the range of the species in California. We did not use climate wizard data to calculate temperature exposure. Rather, we used the temperature grids described below in section D, modeled response. Moisture change is the predicted net change in moisture based on the Hamon AET:PET Moisture Metric climate wizard data, calculated over the range of the species in California.

CCVI Section B: Indirect Exposure

Indirect Exposure evaluates the specific geographical area under consideration and is defined by three categories: 1) exposure to sea level, 2) distribution relative to barriers (natural and anthropogenic), and 3) predicted impact of land use changes resulting from human responses to climate change.

For exposure to sea level rise, we used an on-line interactive sea level rise map created by the Environmental Studies Laboratory at the University of Arizona (http://www.geo.arizona.edu/dgesl/research/other/climate_change_and_sea_level/mapping_slr/). The interactive map highlighted general areas in California that are predicted to be susceptible to a 1-6 meter rise in sea level.

Distribution relative to barriers assesses natural and anthropogenic barriers that may restrict species from dispersing to habitat in new areas. To assess natural barriers we imported elevation and hill shade data into a GIS, from California's Department of Fish and Game GIS library, and looked at the topography surrounding each species and predicted future species distribution maps to determine if natural barriers are present. To assess anthropogenic barriers we downloaded the Wildland Urban Interface provided by the Silvius Lab, University of Wisconsin-Madison and the USDA Forest Service North Central Research Station (<http://silvis.forest.wisc.edu/old/Library/WUILibrary.php>). The Wildland Urban Interface helped determine urban density in surrounding areas and land conversion for agricultural.

To determine predicted impacts of land use changes in response to climate change we looked into strategies designed to mitigate greenhouse gases in California, such as solar power stations, wind farms, geothermal wells and biofuel production sites that may affect species current or future ranges. We imported renewable energy production site layers into a GIS and assessed impacts in areas within or surrounding a species' range. Layers were sourced from the CA Department of Fish and Game's Biogeographic Information and Observation System (BIOS).

CCVI Section C: Sensitivity

Sensitivity to climate change is based on a variety of species-specific factors, including the following:

- dispersal capability
- past climate regime and reliance on specific thermal and hydrological conditions

- dependence on disturbance
- dependence on snow or ice cover
- restriction to certain geological types
- reliance on interspecific interactions (e.g. herbivory and predator/prey relationships)
- genetic variation
- climate-related changes in phenology

Each species is scored by checking a rank of decreased, somewhat decreased, neutral, somewhat increased, increased, or greatly increased (or a subset range of these categories), with three to six of these categories available for each species being assessed. Descriptions of each factor and examples of how to score them are available in additional tabs in the CCVI calculator spreadsheet to help make scoring easier. Some factors are optional, but ten factors in this group must be ranked or the CCVI score is ‘Insufficient Evidence.’

Dispersal and movements pertains to dispersal abilities through non-suitable habitat, and having the ability to follow shifting climate envelopes (Young et al. 2010). To assess species dispersal, we created a vulnerability chart (Table 1) from least to greatest vulnerability based on dispersal mechanisms (and associated distances), and the type of habitat (Continuous or patchy) in which the species is found.

The predicted sensitivity to temperature and moisture changes factor examines the variation in

temperature and precipitation a species has experienced in recent history. It has two parts, physiological hydrologic niche and physiological thermal niche. Historical temperature and precipitation was calculated using Climate Wizard’s historical temperature and precipitation data from 1950-2000.

The dependence on a specific disturbance regime factor identifies disturbance regimes that are likely to be impacted by climate change. For example, forests and riparian corridors maintained by regular disturbances like fires or flooding may be vulnerable to changes in the frequency and intensity of these disturbances caused by climate change. Disturbance was assessed using available data for California fire patterns, and ranked from high to low, based on ecosystem type. The guidelines to this factor are listed in the protocol (Appendix 3).

Dependence on ice, ice-edge, or snow-cover habitats did not play a role in our assessment, because it did not pertain to any of the rare species on our list.

Restriction to uncommon geological features assesses species susceptibility based on restriction to specific substrates, soils, or physical features, such as caves, cliffs, or sand dunes. To assess rare plants, it was important to consider soil endemics, so SSURGO soil data from the NRCS (<http://soildatamart.nrcs.usda.gov>) was layered in a GIS to aid literature in determining substrate restrictions. CNDDDB records and personal field obser-

Table 1. Dispersal scoring criteria. Dispersal mechanisms were grouped into five main types (Vittoz et al. 2007): Greatly increased (GI), increased (I), somewhat increased (SI), neutral (N), somewhat decreased (SD), or decreased (D).

Dispersal	Habitat type	Vulnerability rank
Autochory/ Patchy	Patchy	GI to I
Myrmecochoy/ Patchy	Patchy	GI to I
Myrmecochoy/ Continuous	Continuous	I to SI
Autochory/ Continuous	Continuous	I to SI
Hydrochory/ Patchy	Patchy	SI to N
Zoochory/ Patchy	Patchy	SI to N
Hydrochory/ Continuous	Continuous	N
Anemochory/ Patchy	Patchy	N
Anemochory/ Continuous	Continuous	N to SD
Zoochory/ Continuous	Continuous	N to SD

vations from experts were also considered here.

Reliance on interspecific interactions relates to species having any relationship with other species that are important in some part of their life cycle. Literature and expert opinions were the main source of data for this factor. The subsections are:

- dependence on other species to generate habitat
- pollinator versatility
- dependence on other species for propagule dispersal
- forms part of an interspecific interaction not covered above.

The genetic factor assesses the ability of a species to genetically adapt to environmental changes brought about by climate change. Due to lack of genetic research for most species on our list, this factor was assessed for only two species.

Phenological response refers to responses of organisms to changing seasonal temperature and precipitation dynamics (e.g. earlier onset of spring, longer growing season). In assessing phenological changes, we referred to the California Native Plant Societies rare plant inventory bloom period data (<http://www.rareplants.cnps.org/>). Bloom period data is listed in the on-line individual species profiles. The shorter the bloom period, the more vulnerable a species was considered for this factor. We assessed the species this way due to lack of phenological research for many individual species.

When there was a lack of information for any factor in section C, a protocol (Appendix 3) was used to assess important factors for species with limited available life history data.

After we completed Section C, we turned to botanists for expert opinions on our factor scores and for additional information. We did not have experts to review all the species on our list. We updated our scores when necessary.

CCVI Section D: Modeled Response

We modeled range size change and range overlap

using the Maxent algorithm (Phillips et al. 2006; Elith and Leathwick 2009). Maxent is a statistical model that uses machine learning. We acquired a dataset comprising four climate variables (annual temperature, annual precipitation, seasonality of temperature, and seasonality of precipitation) for current conditions (mean 1970 - mean 2000) and for future conditions (2080; GCM, SRES). Climate data was at 1 km² resolution. We fit a Maxent model for current conditions and used the resulting model to predict climatic suitability, ranging from 0 to 1, for both current and future conditions. These continuous surfaces were then converted to binary (presence/absence) using a threshold. The threshold was determined as the value that maximizes the kappa, a statistical measure of the agreement between predictions and observations. Change in range size was calculated as the sum of area predicted as suitable at time point 2 (t2) minus the sum of area predicted as suitable at time point 1 (t1), divided by the sum of area predicted as suitable at t1. Range overlap was calculated as the sum of area predicted to be suitable at t1 and t2, divided by the sum of area predicted as suitable at t1. The geographic extent of all models was California.

CCVI Risk Factor Score

The distributional and natural history information for each species was entered into the CCVI Excel calculator to obtain vulnerability scores for each species. When the required amount of data in each section (A-D) was complete, the output was one of six vulnerability scores listed in Table 2. A measure of confidence in species information is provided with the final score, which is based on the degree of certainty in the factor values as represented by the frequency of multiple categories of vulnerability being selected for a given factor (Young et al. 2011). In addition, all vulnerability scores were recorded with and without modeled response to climate change to compare CCVI results with and without climate modeling affects on vulnerability.

CCVI Repeatability

To determine if two independent observers

Table 2. Climate change vulnerability index score definitions.

Index Scores	Descriptions
Extremely vulnerable (EV)	Abundance and/or range extent within geographical area assessed extremely likely to substantially decrease or disappear by 2050.
Highly vulnerable (HV)	Abundance and/or range extent within geographical area assessed likely to decrease significantly by 2050.
Moderately vulnerable (MV)	Abundance and/or range extent within geographical area assessed likely to decrease by 2050.
Presumed Stable (PS)	Available evidence does not suggest that abundance and/or range extent within the geographical area assessed will change (increase/decrease) substantially by 2050. Actual range boundaries may change.
Increase likely (IL)	Available evidence suggests that abundance and/or range extent within geographical area assessed is likely to increase by 2050.
Insufficient evidence (IE)	Available information about a species' vulnerability is inadequate to calculate an Index score.

would obtain the same results, we had a second individual (Roxanne Bittman) run species through the CCVI without prior knowledge of the previous ranks. The expert chose 30 familiar species from our list and then randomly chose seven species to score using the CCVI. The expert relied on personal familiarity, field observations, the CNDDDB, and literature review.

CCVI Predictors

We tested if particular factors were statistically associated with the overall CCVI score using regression analysis. We converted the CCVI scores and factor ranks to their numeric equivalents. For each test, we excluded those species that were scored as 'unknown' for the particular factor used in the test. The 'dietary versatility' factor was not applicable as it is not relevant to plants and the factors 'measured genetic variation' and 'bottlenecks in recent evolutionary history' were only scored for two species. So, these factors were excluded, leaving us with 17 total factors to consider. Thus, we examined CCVI scores vs. each of the 17 factors, using a total of 17 regression tests, and tests varied in the number of species included due to the absence of information for particular factors.

Next, we compared the CCVI score with the

California rare plant rank, Rabinowitz's rarity type (Rabinowitz 1981), plant duration, plant growth form, and biogeographic affinity (Raven and Axelrod 1978), using five one-way ANOVAs. We also tested if range size change or range overlap was related to the same five predictors, using 10 one-way ANOVAs.

II. Sensitivity analysis

For each of the 156 species, we ran 22 additional models to estimate the sensitivity of predictions to modeling assumptions. Our 23 models were:

- Model 1: 19 climate variables
- Model 2: 4 climate variables (described above)
- Models 3-14: 4 climate variables, with different GCM*ES combinations
- Model 15: 19 climate variables with soil type
- Model 16: 19 climate variables with soil properties (pH, organic matter, and clay)
- Model 17: 4 climate variables with soil type
- Model 18: 4 climate variables with soil properties (pH, organic matter, and clay)
- Model 19: 4 climate variables, with random forest
- Model 20: 4 climate variables, with random forest, and with a customized geographic

- extent for each species
- Model 21: 4 climate variables with an equal number of presences and psuedo-absences
- Model 22: 4 climate variables, with boosted regression tree
- Model 23: 4 climate variables, with Maxent, and with a customized geographic extent for each species.

Rather than using range size and range overlap to compare model outputs, we sought a metric that could be derived without converting continuous predicted surfaces to binary, because of problems inherent to thresholding when modeling rare species. Thus, we calculated an ‘anomaly score.’ We extracted the suitability values (0 to 1) for each known occurrence at t1 and at t2, and then calculated an anomaly value for each occurrence as the value at t2 minus the value at t1. We then took the mean of these anomaly values and refer to this as the anomaly score for each species. This anomaly score represents the predicted effect of climate change on each species. A negative anomaly means that suitability at t2 will be lower than it was at t1. While this anomaly score is not inserted into the CCVI, it will be used in the sensitivity analysis described below.

For the sensitivity analysis, we asked if the anomaly score was significantly related to the model configuration, within species, using a two-way ANOVA. Tukey’s HSD tests were used for post-hoc means separation by model configuration. We also examined the relationship between anomaly score and CCVI score using linear regressions. Finally, we tested if median anomaly score of each species was related to California rare plant rank, Rabinowitz’s rarity type, plant duration, plant growth form, and biogeographic affinity using five one-way ANOVAs.

III. Topographic complexity analysis

To explore the utility of assessing the amount of topographic variability around known occurrences, we calculated an index of ‘topographic complexity.’ For our index, a species in a topographically complex landscape is considered less vulnerable than a species in a topographically homogeneous

landscape. We calculated the standard deviation of elevations within 100 meters of each occurrence, and then the mean of those values for each species.

We asked if the topographic complexity score was significantly related to the CCVI score using linear regression. We also tested if the topographic complexity score was related to California rare plant rank, Rabinowitz’s rarity type, plant duration, plant growth form, and biogeographic affinity using five one-way ANOVAs.

Finally, we examined the pairwise relationships among anomaly score, topographic complexity, range size change, and range overlap, using six regression analyses.

RESULTS

I. CCVI

Of the 156 species assessed, 99 were determined to be vulnerable (Extremely vulnerable, Highly Vulnerable, or Moderately Vulnerable) to climate change and 48 were determined to be stable or increasing (Presumed Stable or Increase Likely). The distribution of final scores (Fig. 3) was: Extremely Vulnerable ($n = 2$), Highly Vulnerable ($n = 40$), Moderately Vulnerable ($n = 57$), Presumed Stable ($n = 32$), Increase Likely ($n = 16$), and Insufficient Evidence ($n = 9$). All assessment scores and species attribute data are reported in Appendix 1. The top five most vulnerable species, with and without section D (‘modeled response’), are listed in Table 3.

In testing repeatability of the index (Table 4), only two of the seven species assessed by an independent reviewer (Roxanne Bitmann of DFG) differed in the final CCVI score of the original assessor, and only by one score level. For *California macrophylla*, the two observers scored dispersal and physiological hydrological niche differently. For *Allium munzii*, the two observers scored dispersal and disturbance regime differently, which caused the final score to change. The other five species had factors that were marked slightly different, but it did not affect the final score.

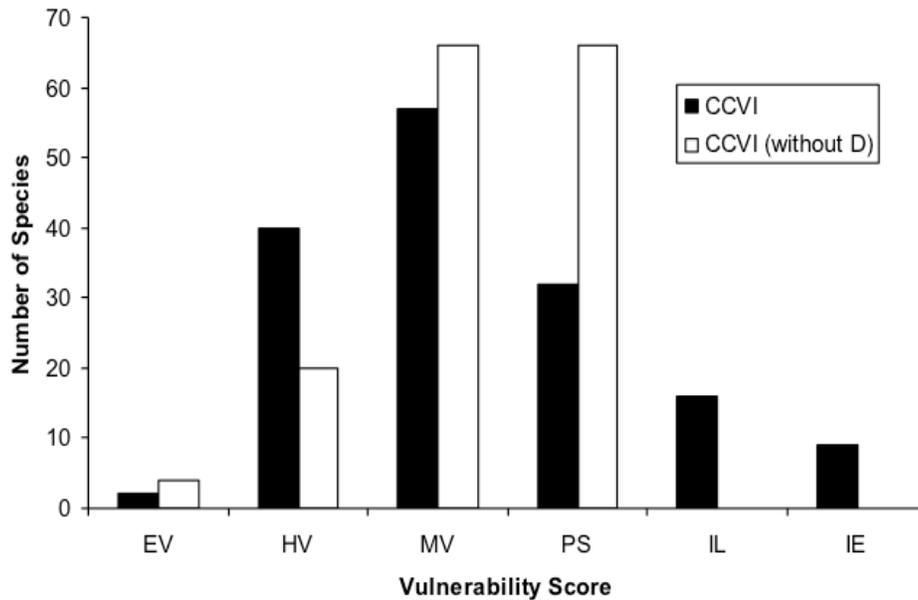


Figure 3. Species rank distributions. CCVI = climate change vulnerability index. D indicates section D of the CCVI (modeled response).

When comparing the CCVI scores of the species with and without section D ('modeled response'), the number of species in each CCVI score level varied (Fig. 5).

For the 156 species assessed, the final CCVI score

was significantly related to just one of the 17 factors that were used to calculate it: anthropogenic barriers (NatureServe factor B2b; $r^2 = 0.09$, $P < 0.001$, $n = 147$). Anthropogenic barriers were ranked as limiting the ability of species to migrate for 99 of the 156 species. We ignore a signifi-

Table 3. Top five most vulnerable species. 'Section D' refers to the modeled response of the CCVI.

Species	CCVI	CCVI (without D)	GRank	SRank	California Rare Plant Rank	Fed_List
Top 5 based on CCVI (with section D)						
1 <i>Piperia yadonii</i>	EV	HV	5	2&3	2	None
2 <i>Mimulus purpureus</i>	EV	HV	4	2.1	2	None
3 <i>Calliandra eriophylla</i>	HV	MV	2	2.2	1B	None
4 <i>Limosella subulata*</i>	HV	HV	2	2.1	1B	Endangered
5 <i>Taraxacum californicum</i>	HV	MV	2	2.1	1B	Endangered
Top 5 based on CCVI (without section D)						
1 <i>Monolopia congdonii</i>	MV	EV	3	3	1B	Endangered
2 <i>Orcuttia viscida</i>	HV	EV	1	1.1	1B	Endangered
3 <i>Pogogyne abramsii</i>	MV	EV	2	2.1	1B	Endangered
4 <i>Symphyotrichum lentum</i>	HV	EV	2	2	1B	None
5 <i>Mimulus purpureus</i>	EV	HV	4	2.1	2	None

**Limosella subulata* may not be native to California.

Table 4. Repeatability results. Climate change vulnerability index scores are presented for seven species that were assessed independently by two people.

Plant species	Assessor 1	Assessor 2
<i>Allium munzii</i>	PS	MV
<i>Astragalus brauntonii</i>	MV	MV
<i>Atriplex joaquiniana</i>	HV	HV
<i>California macrophylla</i>	PS	MV
<i>Limosella subulata</i>	HV	HV
<i>Brodiaea orcuttii</i>	HV	HV
<i>Hesperolinon congestum</i>	PS	PS

cant relationships ‘dependence on other species to generate habitat’, because 97% of the species were scored as neutral. Likewise, we ignore a significant relationship with ‘dependence on other species for propagule dispersal’ because the test only included 13 species. Although not significant, we also note that land use changes from human response to climate change was ranked as increasing climate change vulnerability for 80 species and narrow temperature tolerances (‘historical thermal niche’) were ranked as increasing climate change vulnerability for 80 species.

The CCVI score was not significantly related to California rare plant rank. For example, the 1B species were scored rather evenly as ‘highly vulnerable ($n = 35$), moderately vulnerable ($n = 49$), presumed stable ($n = 30$), and increase likely ($n = 14$) (2 species were scored extremely vulnerable). In addition, the CCVI score was not related to duration, growth form, biogeographic affinity, or Rabinowitz’s rarity type.

Change in range size was not significantly related to California rare plant rank, rarity type, growth form, or biogeographic affinity. Change in range size was significantly related to duration ($P = 0.005$), where annuals had larger increases in range size than perennials. Range overlap was not significantly related to CNPS rare plant rank, rarity type, growth form, or biogeographic affinity. Range overlap was significantly related to duration ($P = 0.02$), where an-

nuals had higher range overlap than perennials.

II. Sensitivity analysis

The anomaly scores statistically differed by species and by model configuration (treatment $P < 0.001$; species $P < 0.001$), where the models with the highest anomalies were those made with Maxent that included soil information and the models with the lowest anomalies are those made with Random Forest.

Anomaly score and CCVI score were significantly related ($r^2 = 0.54$, $P < 0.001$), where species scored as vulnerable also had low anomaly scores. This is not surprising, given CCVI score includes modeled response. In fact, the CCVI score calculated after excluding modeled response is not significantly related to anomaly score. CCVI score and topographic complexity were not significantly related.

Anomaly score was not significantly related to California Rare Plant Rank, rarity type, growth form, or biogeographic affinity. Anomaly score was significantly related to duration ($P = 0.013$), where annuals had higher anomaly scores than perennials.

III. Topographic complexity analysis

Topographic complexity was not significantly related to California Rare Plant Rank or growth form. Topographic complexity was significantly related to rarity type ($P < 0.001$), where habitat specialists had higher topographic complexity than habitat generalists. Topographic complexity was significantly related to duration ($P = 0.05$), where perennials had higher topographic complexity than annuals. Topographic complexity was also significantly related to biogeographic affinity ($P = 0.015$), where members of CFP and NTM had higher topographic complexity values than MaT and WTD.

Range size change and anomaly score were significantly related ($r^2 = 0.39$, $P < 0.001$). Range overlap and anomaly score were significantly correlated ($r^2 = 0.82$, $P < 0.001$). Range overlap

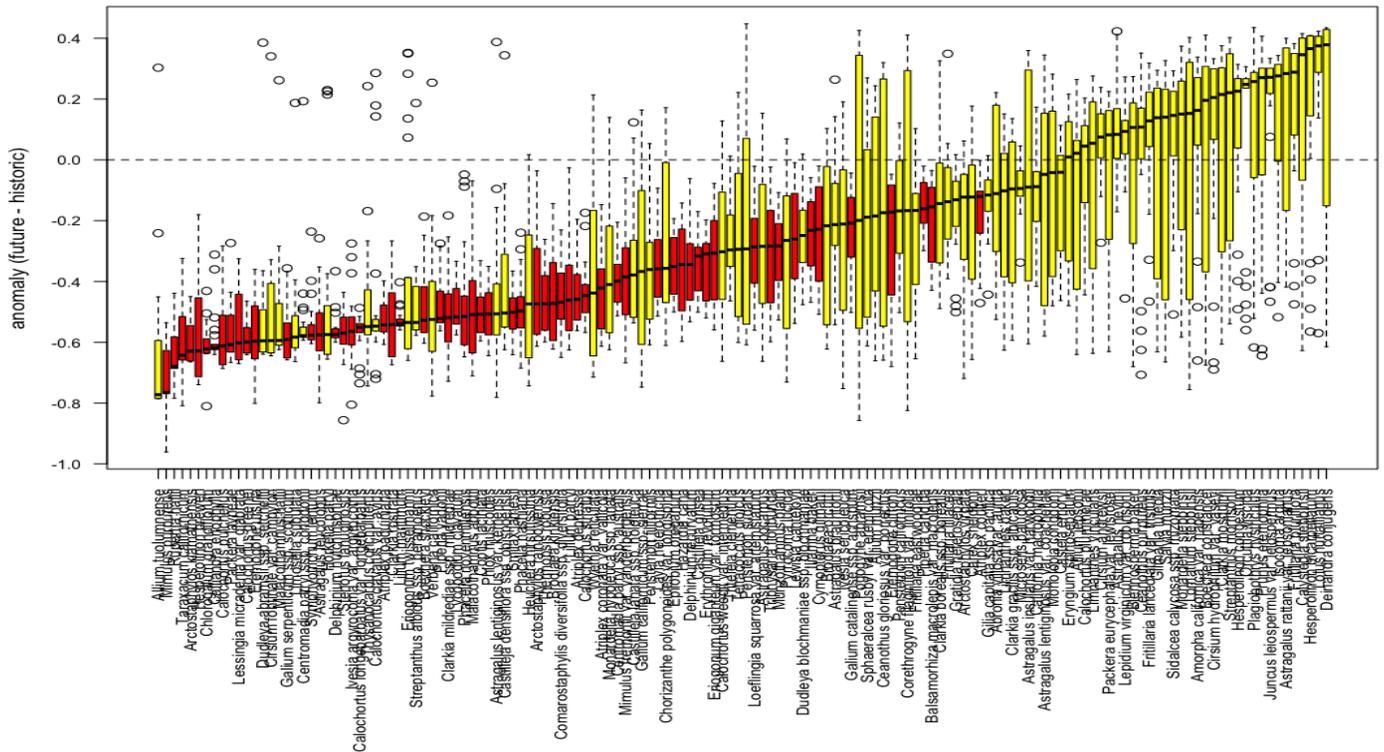


Figure 4. Sensitivity analysis results, by species. The variation in anomaly score across 24 distribution models is represented with box plots, where open circles indicate statistical outliers. Red boxes are those species whose distributions do not cross the horizontal dashed line (anomaly = 0). Yellow boxes are those species whose distributions do cross the horizontal dashed line (anomaly = 0).

and topographic complexity were not significantly correlated ($r^2 = 0.36$, $P < 0.001$). Topographic complexity was not significantly related to anomaly, range size change, or range overlap.

DISCUSSION

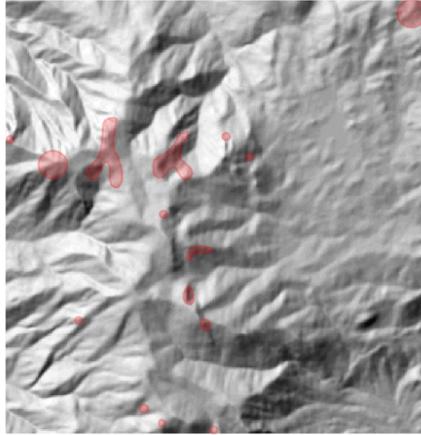
99 of our 156 species were vulnerable to climate change (scored as moderately vulnerable or higher) (Fig. 5). There was little variance in the final scores we assigned and those of a third party, based on a repeat assessment of seven species, which gives us confidence in the repeatability of our work. We present a list of the top five most vulnerable species (Table 3), an attributed species list (Appendix 1). In addition, all the information we used to make our determinations is on-line (see CCVI excel workbooks and species profiles at <http://www.dfg.ca.gov/biogeodata/>).

Only one vulnerability factor from the indirect exposure and sensitivity sections was significantly (but weakly) related to the CCVI scores. The inability to predict the CCVI scores using the indirect exposure and sensitivity factors re-

flects the high importance of direct exposure in calculating the overall CCVI score. This is perhaps unsurprising, given that the indirect exposure and sensitivity factors are weighted by direct exposure in the calculation of the final CCVI score (Young et al. 2011). In other words, direct exposure will be the most important predictor of the CCVI score, by design. In retrospect, this weighting is perhaps undesirable, as it confounds contributions of species attributes, a function of their ecology, with their exposure to climate change, a function of their geographic range. Another reason not to heavily weight exposure is that exposure is based on future climate change predictions, which are uncertain. Also, weighting exposure heavily will tend to overestimate the vulnerability of species that are highly tolerant of shifting climate conditions. While the separate attributes of species traits and species exposure must be combined in some way to create an overall index, a better approach may be to combine them in an additive (rather than multiplicative) way, but also to report the contributions of species attributes and direct exposure separately.

The single factor that was related to the CCVI

A. *Eriogonum twisselmannii*



B. *Limosella subulata*

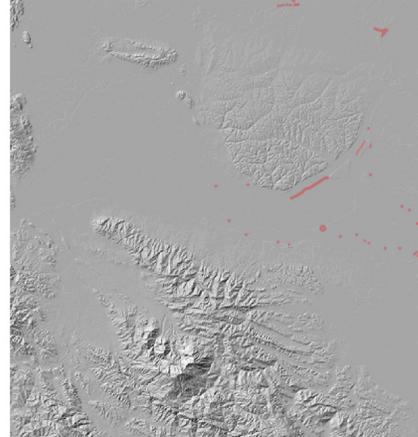


Figure 5. Illustration of topographic complexity. A. *Eriogonum twisselmannii* had an anomaly score of -0.61 and a topographic complexity (st. dev. of elev.) of 27.3. B. *Limosella subulata* had an anomaly score of -0.64 and a topographic complexity score of 0.51.

score was anthropogenic barriers. For 99 of the 156 species, we determined that their ability to migrate to track shifting climate would be impeded due to man-made barriers. This reflects the fact that many rare species are concentrated in coastal areas, where population density and associated fragmentation are extremely high (e.g. San Francisco Bay Area and Los Angeles) (Stein et al. 2000). In California, rare species are more likely in these areas because of natural reasons, including benign climates and habitat heterogeneity, but also because of habitat loss due to development. If these species are unable to tolerate new climate conditions and cannot find refuge from intolerable climates locally, then the likelihood of dispersing to a more favorable, distant location is expected to be very low given man-made barriers. These species are prime candidates for assisted migration (McLachlan et al. 2007).

We found the CCVI scores were independent of the California Rare Plant Rank, rarity type, biogeographic affinity, duration, and growth form. This is a desirable result, as it suggests that the CCVI scores cannot be obtained from pre-existing information. This is perhaps the greatest strength of the CCVI: it represents a framework for thinking exclusively about climate change vulnerability. In developing the CCVI, it was a goal

of NatureServe that the CCVI should be as independent as possible from existing rarity ranking indices, as they acknowledged that the rarest species are not necessarily the most vulnerable to climate change. Rather, it is suggested that the CCVI score can be viewed along side of rarity scores (e.g. California Rare Plant Rank) to identify the most vulnerable and rarest species. We include the CCVI scores, as well as several rarity scores, for our list of 156 species (Appendix 1).

Our range change predictions were highly uncertain. The range of anomaly scores per species was very large (Fig. 3), reflecting sensitivities in modeled response to model configuration (i.e. which variables go into the model and which climate dataset) and model algorithm (i.e. Maxent vs. Random Forest vs. Bioclim). However, 60 of the 156 species had negative anomalies regardless of the model type. That is, for these 60 species, no matter which of the models is chosen, the anomaly is negative, indicating a predicted decline in climatic suitability (red bars of Fig. 3). For the remaining 96 species, the direction of the anomaly depends on the model (yellow bars of Fig. 3). One of the largest sources of uncertainty in modeled response was the algorithm. In particular, random forest always produced the highest anomaly scores. While a researcher could go through the models

species-by-species to decide which is most appropriate given the number of occurrences and their distribution, as well as given the species' ecology and dispersal ability, this is an unfeasible exercise for even a relatively small list of species such as ours. The uncertainty in our modeled results is probably largely due to working with rare species, which have few occurrences (median number of occurrences for our species was 35) and many non-climatic factors that determine their distributions. This reflects the 'rare species modeling paradox,' which says that the species 'most in need of predictive distribution modeling...are the most difficult to model' (Lomba et al. 2010). In other words, while it is extremely important to identify the climatic tolerances of rare species, given our conservation concerns, it is extremely difficult to make meaningful models of the climatic ranges based on the available information.

The uncertainty of the modeled results is concerning because our CCVI scores include modeled results from just one of the models. If we exclude these modeled results from our CCVI scores, the CCVI score can move up or down one score level (e.g. from highly vulnerable to moderately vulnerable or increase likely to presumed stable. See Table 3 and Fig. 6 for an example). For example, none of our species are scored as 'increase likely' if we exclude the modeled results. In other words, the results of that one model have a large impact on the final CCVI score, which is worrisome since modeled results are extremely dependent on model configuration and algorithm. While recent advances in modeling techniques, including consensus modeling, modeling clades instead of species, adding a process models, and accounting for spatial autocorrelation in occurrence data, may help produce a model that better reflects the climatic niches of plants, we expect that a quantitative modeling approach, in isolation, will never be sufficient to accurately predict the fate of rare species to climate change.

When we consider the median anomaly score, we find it is related to plant duration (i.e. annual or perennial), where perennials are predicted to have lower anomalies (i.e. larger reductions in climatic suitability). This suggests the perennials occupy

places where climate change will be the greatest; however, perennials occupy more topographically complex landscapes. If high turnover in local microclimates is associated with high topographic complexity, then these species may be able to find suitable climate locally, despite the fact the climate is changing rapidly in the region. Of course, this 'local-refugia' effect may be only short-lived if climate change is rapid and directional.

Our index of topographic complexity may help create a finer understanding of climate change vulnerability for our species. For example, 41 species are ranked as highly vulnerable, but they have a range of topographic complexity scores. Therefore, we can single out the highly vulnerable species that also have low topographic complexity scores as being especially vulnerable, with the mechanistic explanation that the local topography will not be sufficient to buffer them from region-wide climate change. For example, topographically complex places have been predicted to have slower velocities of climate change, at least when compared at the worldwide scale (Loarie et al. 2009). That said, the relationship between local landscape features and climate is complex and is just beginning to be documented (Dobrowski 2011). Additionally, the interactions among topography, soils, soil water capacity, and microclimate on plant performance remains poorly described, despite that plants are extremely sensitive to such interactions in California.

While we feel that there is much room for improvement on the methods used to conduct species vulnerability assessments, they will always be inherently time consuming. For example, we were able to process only one to two species per eight-hour workday. This rate is far too slow and expensive for most agencies to rollout for all the listed species in the flora and fauna. Our approach of subsetting a larger list based on rarity type had the advantage of possibly identifying particular combinations of range size, population size, and habitat specialism that cross-walk to climate change vulnerability, thus saving us the need to complete the CCVI for the remaining species. However, we found rarity type had no predictive power for the CCVI scores, and thus a detailed

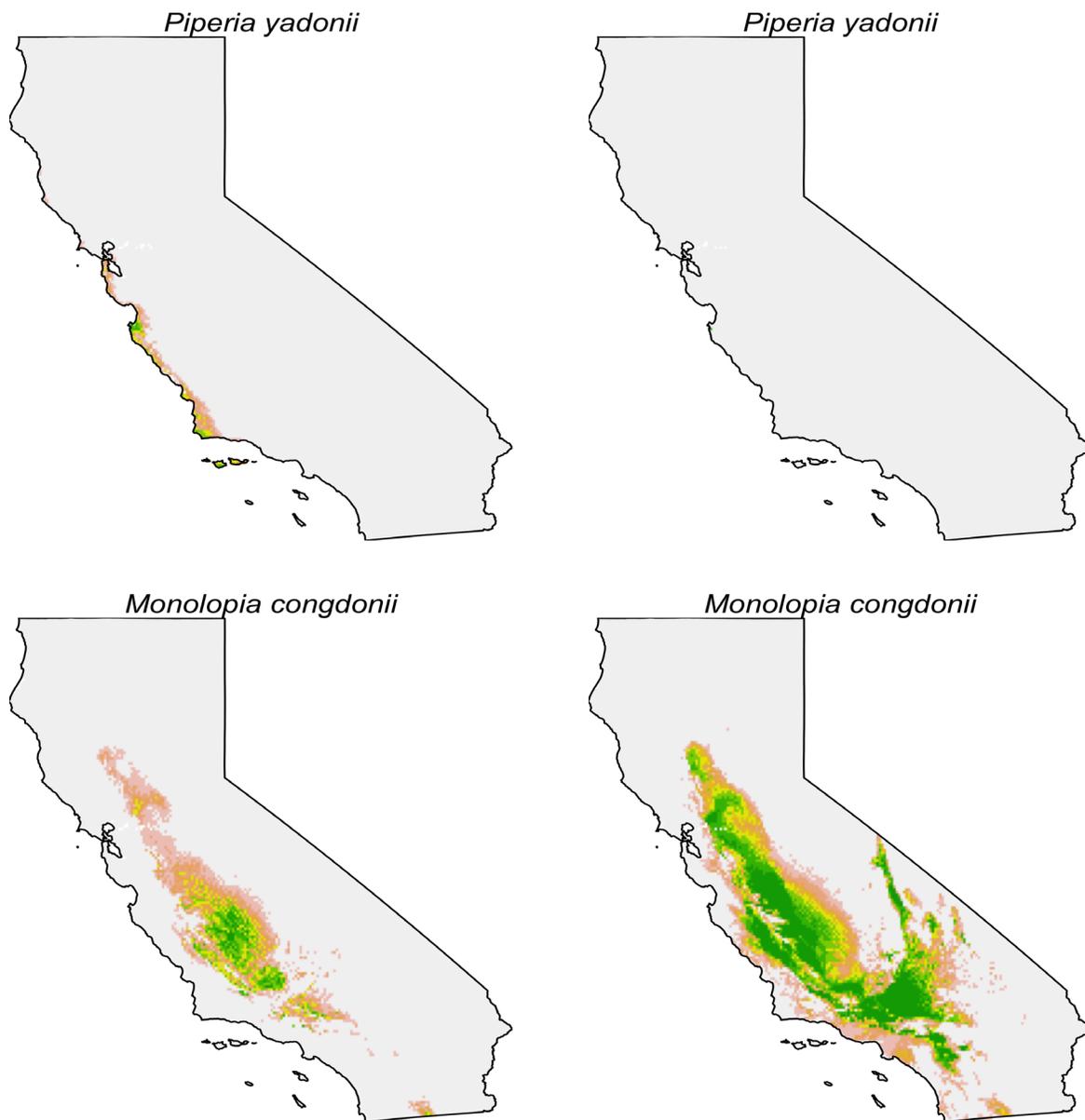


Figure 6. Maps of the predicted current (left column) and future (right column) ranges for two vulnerable species. For *Piperia yadonna*, the predicted range loss causes the overall CCVI score to increase, from highly vulnerable to extremely vulnerable. For *Monolopia congdonii*, the predicted range gain causes the CCVI score to decrease, from extremely vulnerable to moderately vulnerable.

species-level analysis seems necessary to rank species with regards to climate change vulnerability. An alternative or complementary approach is to conduct other types of assessments, including vulnerability of landscape features (topography and connectivity) and habitats. These assessments can be completed relatively easily, and the results are perhaps more reliable, given that the connec-

tion between vulnerability scores to landscape features and habitats is less tenuous than the connection between vulnerability scores to species distributions and species ecologies. For example, most ecologists agree that a well-connected landscape is less vulnerable to climate change than a fragmented landscape, but fewer agree that a species with three pollinators is less vulnerable to cli-

mate change than a species with one pollinator.

CCVI weaknesses

We feel NatureServe's CCVI is an excellent structure and transparent clearinghouse for information regarding climate change vulnerability. To our knowledge, it considers the most exhaustive list of extrinsic and intrinsic factors that may influence vulnerability, and also allows input of model-based results. Further, it is in use by many different groups, allowing for comparison of results. However, we've identified several problems with the CCVI, and have some suggestions for improvements.

As described above, we feel the multiplicative nature of the CCVI is not ideal. The exposure score is calculated using maps of predicted climate change, and reflects the amount of warming or drying a species will 'see,' given its distribution. Given the high level of uncertainties in these predictions, it seems unwise to weight the final vulnerability so heavily towards exposure. Further, the online climate data is coarse for the diversity in California climates. It seems better to weight the sections equally or weight the final vulnerability more towards sensitivity.

A second problem is that some attributes that are important to plant vulnerability are missing, including mating system (selfer vs. out crosser) and pollinator specificity and efficiency. It is recommended that different 'flavors' of the CCVI be released in the future, at least one for animals and one for plants. Third, it is nearly impossible to complete the scoring for a given species, because information is simply lacking. When information is lacking, a species can not be scored unless the guidelines specify to score the species as neutral. This could be misleading. Fourth, some of the scoring guidelines are too simplistic. For example, soil endemics are scored as being more vulnerable to climate change than soil generalists, while this remains a very open research question.

One suggestion for using the CCVI is to adapt the CCVI to your specific needs, project objectives, and available data. The factor questions

are easy to manipulate and rephrase to create factor questions based on available assessment area data. For example, we developed our own rubric for scoring dispersal and disturbance regime. However, customizing the CCVI compromises comparability across projects.

Another idea would be assessing factors such as soil endemism as a natural barrier along with a sensitivity- life history factor. This is one example of a factor the CCVI does not consider a natural barrier. Expert opinions on many species listed unsuitable soil as a natural barrier. Also, the CCVI does not take into account invasive species. Invasive species can become more virulent or less virulent depending on temperature and precipitation changes, and can greatly affect a species native habitat. For example, a recent study showed that climate shifts could increase the dominance of exotic species (Sandel et al. 2011).

Conclusions

We have three key results: (1) 2/3 of our focal species were scored as vulnerable to climate change, (2) modeled range change predictions were highly uncertain, and (3) topographic complexity may be an independent source of information on climate change vulnerability. We expect the information produced via vulnerability assessments like this will be useful in identifying the most vulnerable species to climate change, which can then be carefully monitored. We also think vulnerability assessments are an excellent way to identify knowledge gaps and to form new hypotheses about species distributions and climatic tolerances. Finally, the shortcomings of existing vulnerability indices represent opportunities for improving the believability of the resulting vulnerability rankings.

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REFERENCES

- Burkett, V.R., D.A. Wilcox, R. Stottlemeyer, W. Barrow, D. Fagre, J. Baron, J. Price, J.L. Nielsen, C.D. Allen, and D.L. Peterson. 2005. Nonlinear dynamics in ecosystem response to climatic change: case studies and policy implications. *Ecological Complexity*, 2: 357-394.
- Byers, E., and S. Norris. 2011. Climate Change Vulnerability Assessment of Species of Concern in West Virginia. Report to West Virginia Division of Natural Resources.
- Dobrowski, S.Z. 2011. A climatic basis for microrefugia: the influence of terrain on climate. *Global Change Biology* 17:1022-1035.
- Elith, J. and J.R. Leathwick. 2009. Species distribution models: ecological explanation and prediction across space and time. *Annual Review of Ecology, Evolution, and Systematics* 40: 677-697.
- Foden, W., G. Mace, J.C. Vié, A. Angulo, S. Butchart, L. DeVantier, H. Dublin, A. Gutsche, S. Stuart, and E. Turak. 2008. Species susceptibility to climate change impacts. In: J.C. Vié, C. Hilton-Taylor and S.N. Stuart (eds) *The 2008 Review of The IUCN Red List of Threatened Species*. IUCN Gland, Switzerland.
- Glick, P., B.A. Stein, N.A. Edelson, N.W. Federation, U.S. N.P. Service, U.S.F.W. Service et al. 2011. Scanning the conservation horizon: a guide to climate change vulnerability assessment. National Wildlife Federation, Washington, DC, USA.
- Heller, N.E., and E.S. Zavaleta. 2009. Biodiversity management in the face of climate change: a review of 22 years of recommendations. *Biological Conservation* 142:14-32.
- IPCC. 2007. Climate change 2007: impacts, adaptation and vulnerability. Contribution of Working Group II to the Fourth Assessment Report of the Intergovernmental Panel on Climate Change. Cambridge University Press, Cambridge, UK.
- Kelly, A. E. and M.L. Goulden. 2008. Rapid shifts in plant distribution with recent climate change. *Proceedings of the National Academy of Sciences of the United States of America* 105:11823-11826.
- Klausmeyer K.R., M.R. Shaw, J.B. MacKenzie, D.R. Cameron. In press. Landscape-scale indicators of biodiversity's vulnerability to climate change. *Ecosphere* 2 (8): 1-18.
- Loarie, S.R., B. E. Carter, K. Hayhoe, S. McMahon, R. Moe, C.A. Knight, and D.D. Ackerly. 2008. Climate change and the future of California's endemic flora. *PLoS One* 3:e2502.
- Loarie, S.R., P.B. Duffy, H. Hamilton, G.P. Asner, C.B. Field, and D.D. Ackerly. 2009. The velocity of climate change. *Nature* 462:1052-1055.
- Lomba, A., L. Pellissier, C. Randin, J. Vicente, F. Moreira, J. Honrado, and A. Guisan. 2010. Overcoming the rare species modeling paradox: A novel hierarchical framework applied to an Iberian endemic plant. *Biological Conservation* 143:2647-2657.
- McLachlan, J.S., J.J. Hellmann, and M.W. Schwartz. 2007. A framework for debate of assisted migration in an era of climate change. *Conservation Biology* 21: 297-302.
- Parmesan C. 1996. Climate and species' range. *Nature* 382: 765-766.
- Patwardhan, A., S. Semenov, S. Schnieder, I. Burton, C. Magadza, M. Oppenheimer, B. Pit-

- tock et al. 2007. Assessing key vulnerabilities and the risk from climate change. pp 779-810 in *Climate Change 2007: Impacts, Adaptation and Vulnerability: Contribution of Working Group II to the Fourth Assessment Report of the Intergovernmental Panel on Climate Change*. Cambridge University Press, Cambridge, UK.
- Pearson, R.G. and T.P. Dawson. 2003. Predicting the impacts of climate change on the distribution of species: are bioclimate envelope models useful? *Global Ecology and Biogeography* 12:361-371.
- Phillips, S.J., R.P. Anderson, and R.E. Schapire. 2006. Maximum entropy modeling of species geographic distributions. *Ecological Modelling* 190: 231-259.
- Pounds, J. A., M.R. Bustamante, L.A. Coloma, J.A. Consuegra, M.P.L. Fogden, P.N. Foster, E. La Marca, K.L. Masters, A. Merino-Viteri, R. Puschen-dorf, S.R. Ron, G.A. Sanchez-Azofeifa, C.J. Still, and B.E. Young. 2006. Widespread amphibian extinctions from epidemic disease driven by global warming. *Nature* 439:161-167.
- Rabinowitz, D. 1981. Seven forms of rarity. pp 205-217 in H. Synge (ed) *Aspects of Rare Plant Conservation*. Wiley, New York.
- Raven, P.H., and D.I. Axelrod. 1978. *Origin and Relationships of the California Flora*. Berkeley, University of California Press.
- Sandel, B. and E.M. Dangremond. In press. Climate change and the invasion of California by grasses. *Global Change Biology*.
- Schlesinger, M.D, J.D. Corser, K.A. Perkins, and A.L. White. 2011. *Vulnerability of At-Risk Species to Climate Change in New York*. New York Natural Heritage Program, Albany, NY.
- Stein, B.A., L.S. Kutner, and J.S. Adams (eds) 2000. *Precious Heritage: The Status of Biodiversity in the United States*. Oxford University Press, Oxford, Mass.
- Stralberg, D., D. Jongsomjit, C.A. Howell, M.A. Snyder, J.D. Alexander, J.A. Wiens, and T.L. Root. 2009. Re-shuffling of species with climate disruption: a no-analog future for California birds? *PLoS One* 4:e6825.
- U.S. Environmental Protection Agency (EPA). 2009. A framework for categorizing the relative vulnerability of threatened and endangered species to climate change. <http://www.epa.gov/ncea>.
- Walther, G.R., E. Post, P. Convey, A. Menzel, C. Parmesan, T.J.C. Beebee, J.M. Fromentin, O. Hoegh-Guldberg, and F. Bairlein. 2002. Ecological responses to recent climate change. *Nature* 416:389-395.
- Williams, S.E., L. P. Shoo, J.L. Isaac, A.A. Hoffmann, and G. Langham. 2008. Towards an integrated framework for assessing the vulnerability of species to climate change. *PLoS Biology* 6:e325.
- Young, B.E., E.A. Byers, K. Gravuer, K. Hall, G.A. Hammerson, A. Redder. 2010. NatureServe Climate Change Vulnerability Index Version 2.01 spreadsheet. NatureServe, Arlington, VA. Available: <http://www.natureserve.org/prodServices/climatechange/ccvi.jsp>
- Young, B.E., K.R. Hall, E. Byers, K. Gravuer, G. Hammerson, A. Redder, and K. Szabo. In press. Rapid assessment of plant and animal vulnerability to climate change. In *Conserving Wildlife Populations in a Changing Climate*, edited by J. Brodie, E. Post, and D. Doak. University of Chicago Press, Chicago, IL.
- Vittoz, P. and R. Engler. 2007. Seed dispersal distances: a typology based on dispersal modes and plant traits. *Botanica Helvetica* 117: 109-124.