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Using Two Climate Change Vulnerability Assessment Methods to Prioritize and Manage Rare Plants: A Case Study

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ABSTRACT: Climate change is altering environments where rare plants grow. Assessing species' vulnerability to climate change is important for organizations responsible for managing natural areas and conserving rare species. We assessed the climate change vulnerability of 34 rare plant taxa from the western United States using two methods: NatureServe's Climate Change Vulnerability Index (CCVI) and one based on Species Distribution Modeling (SDM) using Maxent. Of the eight taxa categorized as Extremely Vulnerable by the CCVI, five show significant future loss in each of three SDM measures: change in suitable area, suitable area overlap, and habitat suitability in their present location. Both the CCVI and SDM are important tools to assess climate change vulnerability; each method has complementary strengths that can help land managers make decisions. Here we present examples of how land managers can use SDM and the CCVI in combination to assess climate change vulnerability, to inform rare plant management decisions, and to conserve biological diversity.

Index terms: climate change, climate change vulnerability index, maxent, species distribution modeling, vulnerability assessments

INTRODUCTION

Rapidly changing global land surface temperature and precipitation patterns are altering local environmental conditions where plants grow (IPCC 2007; IPCC 2014). Many plant species are predicted to respond to climate change by shifting their ranges (Parmesan et al. 1999; Kelly and Goulden 2008; Loarie et al. 2008), sometimes moving out of areas that had been protected to conserve their habitat (Heller and Zavaleta 2009). Rapid shifts in species' climatic envelopes will demand new approaches to plant conservation, as simply protecting currently occupied habitats will not suffice for many species. Plant species unable to adapt to rapidly changing conditions or migrate to new areas may be extirpated in parts of their ranges or, in extreme cases, go extinct (IPCC 2007; IPCC 2014).

A suite of strategies has been proposed to address natural resource management under a changing climate (Heller and Zavaleta 2009; Mawdsley et al. 2009). Recent publications provide guidance on the daunting task of incorporating climate change considerations into policy and management plans (AFWA 2009; Glick et al. 2011; NFWPCAP 2012; FAO 2013; Schmitz et al. 2015, this issue). The use of climate change vulnerability assessments to guide decision-making and strategy development has been recommended (Stein et al. 2014). Climate change vulnerability assessments encompass a variety of science-based methods to determine species or habitat vulnerability to climate change. Two approaches are vulnerability indices

and species distribution modeling (Rowland et al. 2011; Johnson 2013).

Vulnerability indices are evaluative frameworks that assess the relative vulnerability of target species to climate change (Rowland et al. 2011). A number of climate change vulnerability indices have been developed (e.g., Bagne et al. 2011). Most vulnerability indices evaluate a combination of a species' exposure, sensitivity, and adaptive capacity to climate change. Exposure can be defined as the magnitude of projected climate change across the species' range within the geographic area assessed. Sensitivity and adaptive capacity are related components of how a species is predicted to respond to climate change. Sensitivity includes life history traits and biotic interactions that govern a species' interaction with its abiotic environment, including climatic conditions. Adaptive capacity can be defined as a species' ability to respond to a changing climate (Rowland et al. 2011).

One example of a vulnerability index widely used in the United States is the Climate Change Vulnerability Index (CCVI) (Byers and Norris 2011; Dubois et al. 2011; Lee et al. 2011; Schlesinger et al. 2011; Walk et al. 2011; Liebezeit et al. 2012; Anacker et al. 2013). The CCVI incorporates factors related to species' direct and indirect exposure and anticipated sensitivity to climate change (Young et al. 2012). Considered a rapid screening method to assess the relative vulnerability of a group of species to climate change, the CCVI evaluates 16 life history traits likely to influence climate sensitivity (e.g., physiological at-

tributes, dispersal mechanisms, pollinator specificity, and geologic substrate fidelity), as well as climate exposure information to predict species' vulnerability to climate change. The CCVI evaluates traits that are indicative of both sensitivity and adaptive capacity, but since these factors can be difficult to tease apart, they are grouped together in one section under the term sensitivity. The CCVI provides insight into why certain plants are more sensitive to climate change than others. Identifying which life history characteristics may impair a species' ability to adapt or migrate provides valuable information for conserving species (Rowland et al. 2011). Using these methods, the most vulnerable species can be targeted for more ambitious conservation measures.

Species distribution modeling (SDM) is a spatial analytic method that uses environmental data to predict current or future areas suitable for species to grow (known as "suitable areas") (Rowland et al. 2011; NFWPCAP 2012). Use of SDM (also known as ecological or environmental niche modeling or climate envelope modeling) has grown rapidly in recent years (Guisan and Thuiller 2005; Cumming 2009; Elith and Leathwick 2009;). Species distribution models aim to map the geographic area where a species may occur by modeling its environmental requirements using indicator variables, such as minimum and maximum temperatures where the species occurs (Elith and Leathwick 2009). For this paper we use the term "suitable area" to indicate those geographic areas where the modeled climatic suitability is above a selected threshold. The suitable area overlap is the portion of the suitable area that is the same in both present and future predictions. Statistical models for climate suitability are generated by relating current locations of occurrences to contemporary climatic variables. Models are validated through a process of predicting suitable habitat area under current climate and comparing predictions with known occurrence data. Well-supported models can then be used to predict future suitable areas under different climate change scenarios (Elith and Leathwick 2009). These models provide detailed information about predicted shifts in suitable area. For example, a common

prediction is that the equatorward edge of species' suitable area will contract and the poleward edge will expand, causing latitudinal shifts in distribution (Parmesan et al. 1999; Hickling et al. 2005). Shifts along latitudinal and elevational gradients are predicted for many taxa. Spatial, climatic, and environmental variables may also interact in complex ways, leading some species to undergo unanticipated changes in distribution (Loarie et al. 2008; Chen et al. 2011; Crimmins et al. 2011; Dobrowski et al. 2011).

In addition to predicting changes in suitable area, SDM can also be used to make more nuanced inferences about shifts in habitat quality. Areas predicted to become more or less suitable in the future are termed the "leading edge" and "trailing edge" of a species' range, respectively. Management strategies for these two edges may be quite different. For example, efforts in the leading edge could focus on forward-looking habitat conservation and reserve design (Heller and Zavaleta 2009). In contrast, the trailing edge may comprise particularly important collection localities for ex situ conservation (Davis et al. 2012), as it is these populations where climate-driven extirpation is most likely to occur.

Two conventional ways of quantifying predicted effects of climate change on species distribution are changes in range size and range overlap (Thomas et al. 2004; Hijmans and Graham 2006; Schwartz et al. 2006; Anacker et al. 2013; Maggini et al. 2014). These are calculated by generating maps of suitable and unsuitable habitat. While intuitive, such predictions require setting a threshold value for differentiating suitable vs. unsuitable, which can be particularly challenging with rare species (Hijmans 2012). The choice of threshold, while beyond the scope of this manuscript, can have dramatic effects on model accuracy and prevalence (Freeman and Moisen 2008). Range overlap is a useful measure that indicates those areas where the suitable habitat is stable over time. Another measure used to compare model predictions is the "suitability score," which is a slight derivation of the anomaly score described by Anacker et al. (2013). The suitability score is calculated as the ratio of the difference

between the current and future suitability for all occurrences for each species. A decrease in the suitability score indicates that the species is more vulnerable in the future. In comparison to the change in range or range overlap, the suitability score reduces assumptions and errors because it does not require deciding upon a, perhaps, tenuous threshold value. In addition, the suitability score is based solely on habitat suitability at known occurrence locations. This is important because it allows land managers to understand how the suitability will change where a species presently occurs. The manager does not have to consider predicted areas of suitable habitat where a species may occur in the future that are outside the current range.

The SDM measures described above, change in range size, range overlap, and suitability score, each serve as useful indicators of vulnerability to climate change. However, it can be cumbersome to interpret each separately, determine how they relate to each other, or to assign precedent in cases where they may show differing patterns. Rather than quantifying vulnerability using multiple measures, Maggini et al. (2014) recently introduced a composite index to integrate across different SDM-based indicators of vulnerability to climate change. We adapt their approach in developing an "SDM score" index.

The purpose of this manuscript is to illustrate how to use SDM and the CCVI to assess a plant species' vulnerability to climate change. Choosing the right assessment method ultimately depends on the goals of the project and the available resources. For example, species groups with little published information on life history characteristics would be difficult to assess based on sensitivity to climate change. Likewise, modeling the distribution of species based on few spatial occurrences would yield results with high levels of uncertainty. In addition, the choice of variables used in SDM can greatly influence the model quality and results (Araújo and New 2007). Used together, the two approaches can cross-validate results and decrease uncertainty, resulting in increased confidence and a greater context in which to interpret results. Combining detailed in-

formation on sensitivity to climate change from the CCVI with spatial data on predicted range shifts from SDM provides a more holistic assessment. These combined analyses of life history characteristics and traits, specific threats to species, and climate change predictions are increasing in use because they result in better informed management actions and a more robust basis for prioritizing those species most in need of protection (Heikkinen et al. 2009; Murray et al. 2011; Gonzalez-Suarez et al. 2013; Garcia et al. 2014).

MATERIALS AND METHODS

Species Selection

We chose 34 plant taxa endemic to the western United States based on NatureServe Global Rank rarity categories (G1/Critically Imperiled, G2/Imperiled, or G3/Vulnerable) comprising species expected to be most vulnerable (Faber-Langendoen et al. 2012). The US Fish and Wildlife Service lists 11 of the 34 taxa as Threatened or Endangered under the Endangered Species Act (Table 1). Taxa presented here are from two independent projects assessing vulnerability to climate change. One project utilized SDM (a subset of results are presented here) and the other utilized the CCVI (Treher et al. 2012; NatureServe, unpubl. data). Both assessed hundreds of taxa designated to be of management concern by the US Department of Interior's Bureau of Land Management. We deliberately chose taxa encompassing diverse life history characteristics in order to highlight how the different vulnerability assessments are influenced by these factors.

Assessing Vulnerability with the Climate Change Vulnerability Index (CCVI)

We assessed all species with the CCVI version 2.1 (Young et al. 2011). We reviewed and scored each factor according to guidance and criteria set by the CCVI (Young et al. 2011; Young et al. 2012). The CCVI evaluates exposure (direct and indirect) and species' sensitivity to climate change. The CCVI assigns an overall vulnerability category ranging from Extremely

Vulnerable to Not Vulnerable/Increase Likely. A score of Insufficient Evidence is assigned if minimum data requirements are not met. Since the CCVI requires a range map for every species assessed, we digitized published range maps from various sources (e.g., FNA 1993+; GCA 2011, see Treher et al. 2012 for details). If we could not find a published range map, we produced one by drawing a minimum convex polygon around occurrence data from various sources (e.g., NatureServe 2011; SEINet 2011) to delineate the range (Treher et al. 2012).

We used ArcGIS 10.0 and 10.1 (ESRI 2011) to calculate each species' direct exposure to future climate projections provided by ClimateWizard (2011a, b) for the A1B emissions scenario, an ensemble average of 15 Global Circulation Models from the 4th Assessment Report of the Intergovernmental Panel on Climate Change (IPCC 2007), which is downscaled to a resolution of roughly 12 km² for a mid-century (2040–2069) time horizon (Young et al. 2011). The CCVI assesses indirect exposure by evaluating species' distributions relative to predicted sea level rise and to natural and anthropogenic barriers that may limit a species' ability to shift its range in response to climate change. For plant species, the CCVI evaluates up to 14 factors (Table 2) related to sensitivity and adaptive capacity including life history characteristics such as dispersal ability, disturbance regimes, and geological affinities. Historical thermal niche and historical hydrological niche were assessed with ArcGIS 10.0 or 10.1 (ESRI 2011) using data from ClimateWizard, as above, to calculate the variation in annual temperature and precipitation across each species' range. A minimum of 10 sensitivity factors must be scored in order for the CCVI to generate an overall assessment category (Table 2).

For this study, we excluded five optional factors from our CCVI assessments to better compare CCVI and SDM results (Table 2). We excluded the CCVI factors relating to documented or modeled responses to climate change because we wanted to compare two methods that did not overlap. We also excluded the factor

assessing predicted indirect impacts such as habitat loss due to the construction of alternative energy facilities and sea walls. This factor is considered in other measures of extinction risk such as Global Ranks.

Assessing Vulnerability with Species Distribution Modeling

We obtained Element Occurrence data for each taxon from NatureServe (2011). Since Element Occurrences represent areas where a species is (or was) present, we converted spatial polygon data to point data needed for SDM by using the centroid of each occurrence. We fit distribution models using Maxent 3.3.3k (Phillips et al. 2006) through the dismo package (Hijmans et al. 2013) in R 2.15 (R Core Team 2012) and using default "auto features" allowing linear, quadratic, product, threshold, and hinge features. Each model run for each climate scenario (including baseline) by species combination consisted of 10 replicates. A threshold value for each model was calculated as the value that maximizes the kappa (MaxKappa), a statistical measure of the agreement between predictions and observations (Cohen 1960; Jiménez-Valverde 2011). We averaged the threshold values and model projections across the replicates for current and future distributions. We used the threshold value to convert the logistic output predictions of climate suitability from continuous to binary (suitable/unsuitable) values. The geographic extent for all models and projections was the convex hull of species' occurrences plus a 50-km buffer. The 50-km buffer is based on maximum expected plant migration rates. For example, historical plant migration rates have been estimated to be 10–30 km per century (McLachlan et al. 2005; Yansa 2006) and Notaro et al. (2012) used a 100-km buffer to examine predicted range shifts by the end of the 21st century. We used a predictor data set acquired from WorldClim (Hijmans et al. 2005) for both contemporary conditions (mean 1950–mean 2000) and future projections at 30 arc-second (~1 km²) resolution. A ranked subset of 10 of the 19 Bioclim variables was selected that are considered broadly important ecological variables for western species (Austin 2007). From this list we chose five variables that were

Table 1. Plant family, NatureServe Global Rank, and US Endangered Species Act (ESA) status for 34 taxa in this study. NatureServe Global Rounded Ranks: Critically Imperiled (1), Imperiled (2), Vulnerable (3), or Apparently Secure (4). 'G' and 'T' indicate the Global Rank at the species and infraspecific taxon levels, respectively. ESA status: Listed Threatened (LT) or Listed Endangered (LE).

Taxon	Common Name	Family	Global Rank	ESA Status
<i>Antennaria arcuata</i> Cronquist	Meadow pussytoes	Asteraceae	G3	-
<i>Arctomecon humilis</i> Coville	Dwarf bear-poppy	Papaveraceae	G1	LE
<i>Arctomecon merriamii</i> Coville	White bear-poppy	Papaveraceae	G3	-
<i>Astragalus micromerius</i> Barneby	Chaco milkvetch	Fabaceae	G3	-
<i>Astragalus remotus</i> (M.E. Jones) Barneby	Spring Mountain milkvetch	Fabaceae	G2	-
<i>Chlorogalum grandiflorum</i> Hoover	Red Hills Soaproot	Poaceae	G3	-
<i>Chorizanthe cuspidata</i> var. <i>villosa</i> (Eastw.) Munz	San Francisco spineflower	Polygonaceae	G2T2	-
(Castetter, Pierce, & K. H. Schwer.) L.D. Benson	Kuenzler hedgehog cactus	Cactaceae	G4T1	LE
<i>Erigeron supplex</i> A. Gray	Supple fleabane	Asteraceae	G2	-
<i>Hemizonia halliana</i> D.D. Keck	Hall's tarweed	Asteraceae	G2	-
<i>Howellia aquatilis</i> A. Gray	Water howellia	Campanulaceae	G3	LT
<i>Lomatium attenuatum</i> Evert	Tartip desertparsley	Apiaceae	G3	-
<i>Monardella robinsonii</i> Epling ex Munz	Robinson's monardella	Lamiaceae	G3	-
<i>Panicum mohavense</i> Reeder	Mojave panicgrass	Poaceae	G2	-
<i>Pediocactus bradyi</i> L.D. Benson	Brady pincushion cactus	Cactaceae	G1	LE
<i>Pediocactus despainii</i> S.L. Welsh & Goodrich	San Rafael cactus	Cactaceae	G2	LE
<i>Pediocactus paradinei</i> B.W. Benson	Kaibab Plains cactus	Cactaceae	G1	-
<i>Pediocactus peeblesianus</i> subsp. <i>fickeiseniorum</i> (L.D. Benson) Lüthy	Fickeisen Plains cactus	Cactaceae	G2T2	LE
<i>Pediocactus sileri</i> (Engelm. ex J.M. Coult.) L.D. Benson	Siler pincushion cactus	Cactaceae	G2	LT
<i>Pediocactus winkleri</i> K.D. Heil	Winkler cactus	Cactaceae	G2	LT
<i>Penstemon albomarginatus</i> M.E. Jones	White-margined beardtongue	Plantaginaceae	G2	-
<i>Penstemon platyphyllus</i> Rydb.	Broadleaf beardtongue	Plantaginaceae	G2	-
<i>Phacelia anelsonii</i> J.F. Macbr.	Aven Nelson's phacelia	Boraginaceae	G2	-
<i>Phacelia insularis</i> var. <i>continentis</i> J.T. Howell	North Coast phacelia	Boraginaceae	G2T1	-
<i>Prunus eremophila</i> Prigge	Mojave desert plum	Rosaceae	G1	-
<i>Sclerocactus glaucus</i> (K. Schum.) L.D. Benson	Colorado hookless cactus	Cactaceae	G2	LT
<i>Sclerocactus spinosior</i> (Engelm.) D. Woodruff & L.D. Benson	Desert valley hookless cactus	Cactaceae	G2	-
<i>Sclerocactus wetlandicus</i> Hochstätter	Uinta Basin hookless cactus	Cactaceae	G3	LT
<i>Sclerocactus wrightiae</i> L.D. Benson	Wright fishhook cactus	Cactaceae	G2	LE
<i>Shoshonea pulvinata</i> Evert & Constance	Shoshone carrot	Apiaceae	G3	-
<i>Spiranthes infernalis</i> Sheviak	Ash Meadow lady's tresses	Orchidaceae	G1	-
<i>Streptanthus brachiatus</i> F.W. Hoffm. subsp. <i>brachiatus</i>	Socrates mine jewelflower	Brassicaceae	G2T1	-
<i>Townsendia spathulata</i> Nutt.	Sword Townsend daisy	Asteraceae	G3	-
<i>Wyethia reticulata</i> Greene	El Dorado mule-ears	Asteraceae	G2	-

Table 2. Climate Change Vulnerability Index (CCVI) factors related to direct exposure, indirect exposure, sensitivity and adaptive capacity, and documented responses to climate change. See Young et al. (2011) for further descriptions of the factors. Text in parentheses indicates the minimum number of factors required per section to calculate an overall vulnerability score.

Direct Exposure (2 factors required)
Predicted changes in temperature
Predicted changes in moisture
Indirect Exposure (3 factors required)
Exposure to sea level rise
Distribution relative to natural barriers
Distribution relative to anthropogenic barriers
Predicted impact of land use changes resulting from human responses to climate change (omitted from this study)
Sensitivity and Adaptive Capacity (10 factors required)
Dispersal and movements
Historical thermal niche
Physiological thermal niche
Historical hydrological niche
Physiological hydrological niche
Dependence on a specific disturbance regime likely to be impacted by climate change
Dependence on ice, ice-edge, or snow-cover habitats
Restriction to uncommon geological features or derivatives
Dependence on other species to generate habitat
Pollinator versatility
Dependence on other species for propagule dispersal
Interspecific interactions not covered above
Measured genetic variation or occurrence of bottlenecks in recent evolutionary history
Phenological response to changing seasonal temperature or precipitation dynamics
Documented or Modeled Responses to Climate Change (optional)
Documented response to recent climate change
Modeled future (2050) change in population or range size
Overlap of modeled future (2050) range with current range
Occurrence of protected areas in modeled future (2050) distribution

not highly correlated with other included variables ($r < 0.6$; Table 3) (Braunisch et al. 2013). For example, mean temperature during wettest quarter could be important for plants in a Mediterranean climate; this predictor variable was chosen over mean annual temperature, with which it was highly correlated. For each model replicate, we chose new random samples for both training data (a randomly selected 75% of the dataset) and testing data (the remaining 25%). Models were evaluated using the Area Under the Curve of Receiver-Operating Characteristic (AUC) and a corrected AUC (cAUC) (Hijmans 2012), a variant on AUC that helps to ac-

count for spatial bias in model evaluation. With the cAUC, a null model (nAUC) is created using random background testing points that are equidistant from training

Table 3. Environmental variables used in the species distribution modeling.	
Variable ID	Variable
BIO2	Mean Diurnal Range*
BIO8	Mean Temperature of Wettest Quarter
BIO10	Mean Temperature of Warmest Quarter
BIO12	Annual Precipitation
BIO17	Precipitation of Driest Quarter
* Mean of monthly (max. temp - min. temp)	

presences. When the nAUC is > 0.5, the AUC is corrected by reducing the AUC by nAUC minus 0.5.

For the future SDM, we evaluated 13 future climate model scenarios (CMS) according to the IPCC 4th Assessment (IPCC 2007) for the 2050s (mean 2040–mean 2069) and derived from seven global circulation models (GCMs), CCCMA CGCM2, CCCMA CGCM3.1, CSIRO MK2, HCCPR HADCM3, INM CM3.0, MIROC3.2, and NIES 99. The combinations of GCM and emissions scenarios (ES), high (A2A), intermediate (A1B) and low (B2A), are outlined in Appendix 1. Each of the 10 distribution model replicates was used to project future climatic suitability for each CMS. Results presented here (Table 4; Appendix 2) are averages of all model results for each species. Although an updated IPCC climate assessment was recently published (IPCC 2014), we used the IPCC's Fourth Assessment (2007) in order to maintain common datasets for both the CCVI and SDM.

Modeled Response to Climate Change

Suitable areas, present (t_1) or future (t_2), are those areas predicted to be suitable based on the methods described above. To quantify each taxon's predicted distributional response to climate change, we calculated the difference between the size of suitable area at t_1 and t_2 (change in suitable area), spatial overlap of suitable area at t_1 and t_2 (suitable area overlap), and a third measure called a suitability score.

Change in suitable area measures the amount of contraction or expansion of the modeled distribution between t_1 and t_2 . As the species modeled here have vastly different current suitable areas (50–21,000 km²), the change in suitable area is calculated as a percentage to show relative gain or loss of suitable habitat area. Values for the change in suitable area range from –100% to >5,000%; –100% indicates a complete loss of suitable area and positive values indicate increases in suitable area. Change in suitable area was calculated as follows:

$$\text{Change in suitable area} = [(Area_{t_2} - Area_{t_1}) / Area_{t_1}] \times 100$$

Suitable area overlap is the percentage of the suitable area that overlaps between t_1 and t_2 . A low percentage of suitable area overlap indicates that the suitable area is predicted to contract or shift in the future. Values range from 0 to 1, where 0 indicates no overlap in suitable area and 1 indicates that the entire area suitable at t_1 will remain suitable at t_2 . Suitable area overlap was calculated as follows:

$$\text{Suitable area overlap} = [(\text{overlapping } Area_{t_1} \text{ and } Area_{t_2}) / Area_{t_1}] \times 100$$

The suitability score represents the change in climatic suitability between the present and the future at known occurrence locations. The suitability score for all occurrences was calculated as the anomaly value of the predicted suitability at t_1 subtracted from the predicted suitability at t_2 proportional to the suitability at t_1 . The mean of these values across all occurrences for each species and each model is the change in suitability for each species-model combination. The suitability score used here represents the *proportion* of change from the suitability at t_1 , whereas the anomaly score from Anacker et al. (2013) represents only the change in suitability. Values are continuous and range from –1 to 1, with negative values indicating that the average suitability at the species' present location is predicted to decrease in the future. The suitability score was calculated as follows:

$$\text{Suitability score} = (\text{Suitability}_{t_2} - \text{Suitability}_{t_1}) / \text{Suitability}_{t_1}$$

Consistent with the vulnerability index presented by Maggini et al. (2014), the SDM score measures vulnerability based on multiple indicator variables and scales from 0 (species not vulnerable) to 1 (species highly vulnerable). The first two measures are the same as the calculations from Maggini et al. (2014) functions 1 and 2. The first measure (V_a) calculates the relative amount of change between t_1 and t_2 .

$$V_a = Area_{t_1} / (Area_{t_2} + Area_{t_1})$$

The second measure (V_o) calculates the

relative overlap of suitable area between t_1 and t_2 . The more disconnected the suitable area is between t_1 and t_2 , the more difficult it is to colonize the future area.

$$V_o = 1 - Area_{t_1} / (Area_{t_2} + Area_{t_1})$$

The last indicator presented here (V_s) measures the relative difference for the suitability between t_1 and t_2 and is created by scaling the suitability score from 0 to 1:

$$V_s = 1 - [(\text{suitability score} + 1) / 2]$$

The three indicators are averaged to provide the SDM score:

$$\text{SDM score} = [(V_a + V_o) / 2 + V_s] / 2$$

Correspondence Between CCVI and SDM

To determine if there were significant relationships between CCVI scores and SDM measures, we used Spearman's rank correlation coefficient to compare a numerical CCVI score to the SDM score, suitable area percentage, and suitability score. The CCVI score is normally presented as a categorical scale ranging from Extremely Vulnerable to Increase Likely. Underlying this categorical score is a numerical sum of subscores for each of the extrinsic and intrinsic species sensitivity factors weighted by exposure. Since both the CCVI and SDM incorporate information about exposure to projected climate change, we modified the CCVI numerical score to remove the weight assigned by exposure. We used the resulting "unweighted CCVI score" to compare the CCVI to the SDM using Spearman's Rho.

Correspondence Between SDM, CCVI, Global Ranks, and ESA Listing Status

To evaluate whether traditional measures of extinction risk or legal status can predict vulnerability to climate change, we tested if the Global Rank (G1, G2, or G3) or Endangered Species Act (ESA) status (listed as Threatened or Endangered/not listed) was related to change in suitable area, suitable area overlap, suitability score, and SDM

score for each species using Kruskal-Wallis Tests. Similarly, we evaluated if the Global Rank or ESA listing status was related to the categorical CCVI score using Fisher's Exact Test.

RESULTS

CCVI Results

The CCVI indicated that the majority of the 34 vascular plants assessed are vulnerable to climate change across their entire ranges within the conterminous United States (23% categorized as Extremely Vulnerable, 21% as Highly Vulnerable, and 32% as Moderately Vulnerable) (Figure 1, Table 4). Eight plants were assessed as not vulnerable to climate change (Presumed Stable) by the CCVI. No taxa were scored as Increase Likely or Insufficient Evidence by the CCVI.

SDM Results

Results from the SDM also indicated that the majority of species evaluated were likely more vulnerable to climate change, evidenced by 24 of 34 species with an SDM score >0.5 . For the SDM score, 15 taxa were between 0.75–1.00, 9 were between 0.50–0.75, 7 were between 0.25–0.50, and 3 were between 0.00–0.25 (Table 4). Of the 16 species with a decrease in suitable area, 15 had an overlap of $<50\%$ and all had a lower Suitability Score (Figure 1, Table 4). Of the 18 species with an increase in suitable area, 9 had an overlap of $>50\%$ and 7 had a higher Suitability Score (Figure 1, Table 4).

All SDM model iterations ran to convergence. The cAUC values for 15 species were greater than 0.9, between 0.8 and 0.9 for 9 species, and between 0.7 and 0.8 for 7 species (Appendix 2). Three species had cAUC values less than 0.7.

Correspondence Between CCVI and SDM

The Spearman's rank correlation coefficient showed a significant positive relationship between the unweighted CCVI

score and the SDM score ($r_s = 0.308$, $P = 0.038$). There were significant negative relationships between the unweighted CCVI score and suitable area percentage ($r_s = -0.307$, $P = 0.039$) and the unweighted CCVI score and suitability score ($r_s = -0.318$, $P = 0.033$). Even though these relationships are statistically significant, the Spearman's correlation coefficient (r_s) indicates weak correlations for each pair of factors. Means for the comparisons are presented in Appendix 3.

Relationship Between Global Rank or Listing Status and Vulnerability to Climate Change

Neither Global Rank nor ESA status were significantly related to suitable area, suitable area overlap, suitability score, SDM score, or unweighted numerical CCVI score ($P < 0.05$; data available upon request). Means for the comparisons are presented in Appendix 3.

DISCUSSION

CCVI and SDM as Complementary Methods

Here we synthesize the results of the CCVI and SDM in the context of conserving the taxa assessed in this study. By focusing on a few taxa of interest, we provide examples of how both the CCVI and SDM can be used to inform species conservation.

The CCVI provides a score that reflects a species' predicted vulnerability to midcentury climate change in the species' present range within an assessment area. While the CCVI score is straightforward and descriptive, the value of the CCVI stems from the complex set of factors assessed to arrive at that score. These factors not only provide managers with useful information, but can also be important when interpreting the SDM results. For example, *Arctomecon humilis* (Figure 2A) was assessed as Extremely Vulnerable with the CCVI while the SDM score (0.325) indicates it is relatively less vulnerable (Figure 1). *Arctomecon humilis* is endemic to gypsiferous shale, one factor contributing to its vulnerable CCVI score. If the required

soil type is not present in the predicted future suitable area, the species may not colonize or survive in the new area. Soil is not the only factor that could limit the future distribution of a species. The seeds of *A. humilis* are ant dispersed (Allphin et al. 1998) and, therefore, its rate of migration is likely slower than a species with wind or bird-dispersed seeds. The suitable area overlap is high (82%), so short term management should focus on monitoring existing populations for signs of climate stress. If monitoring data show that populations are declining, assisted migration into gypsiferous shale sites in the future suitable area could be considered due to the species' limited dispersal ability. Life history traits, such as soil endemism and seed dispersal, provide important context to the range shifts predicted by modeling measures (Fordham et al. 2012). This example shows that the SDM approach alone could underestimate climate vulnerability since it does not consider life history traits. Therefore, examining both the CCVI and SDM in combination helps inform management plans.

Predicting vulnerability to climate change with both SDM and the CCVI can validate one another, decreasing uncertainty. An example of this is found with *Pediocactus peeblesianus* subsp. *fickeiseniorum* (Figure 2B), an endemic to Kaibab limestone in northwestern Arizona and the Colorado Plateau that was recently listed as Endangered under the ESA (USFWS 2013b). This taxon had a CCVI score of Extremely Vulnerable and a highly vulnerable SDM score of 0.896 (with a 94% predicted decrease in suitable area, no overlap, and a suitability score of -0.627) (Figure 1). Exacerbating this loss of suitability are natural barriers to dispersal like canyons and mountains. Although little is known about its dispersal mechanism, seed production is low and populations are disjunct, suggesting dispersal rates into new areas will be infrequent (NatureServe, unpubl. data). While reproduction has not been studied in detail for this taxon, other *Pediocactus* species require cross-pollination for seed production and are primarily pollinated by halictid bees (USFWS 2013b). Reliance on a specific pollinator or group of pollinators increases a species' vulnerability to

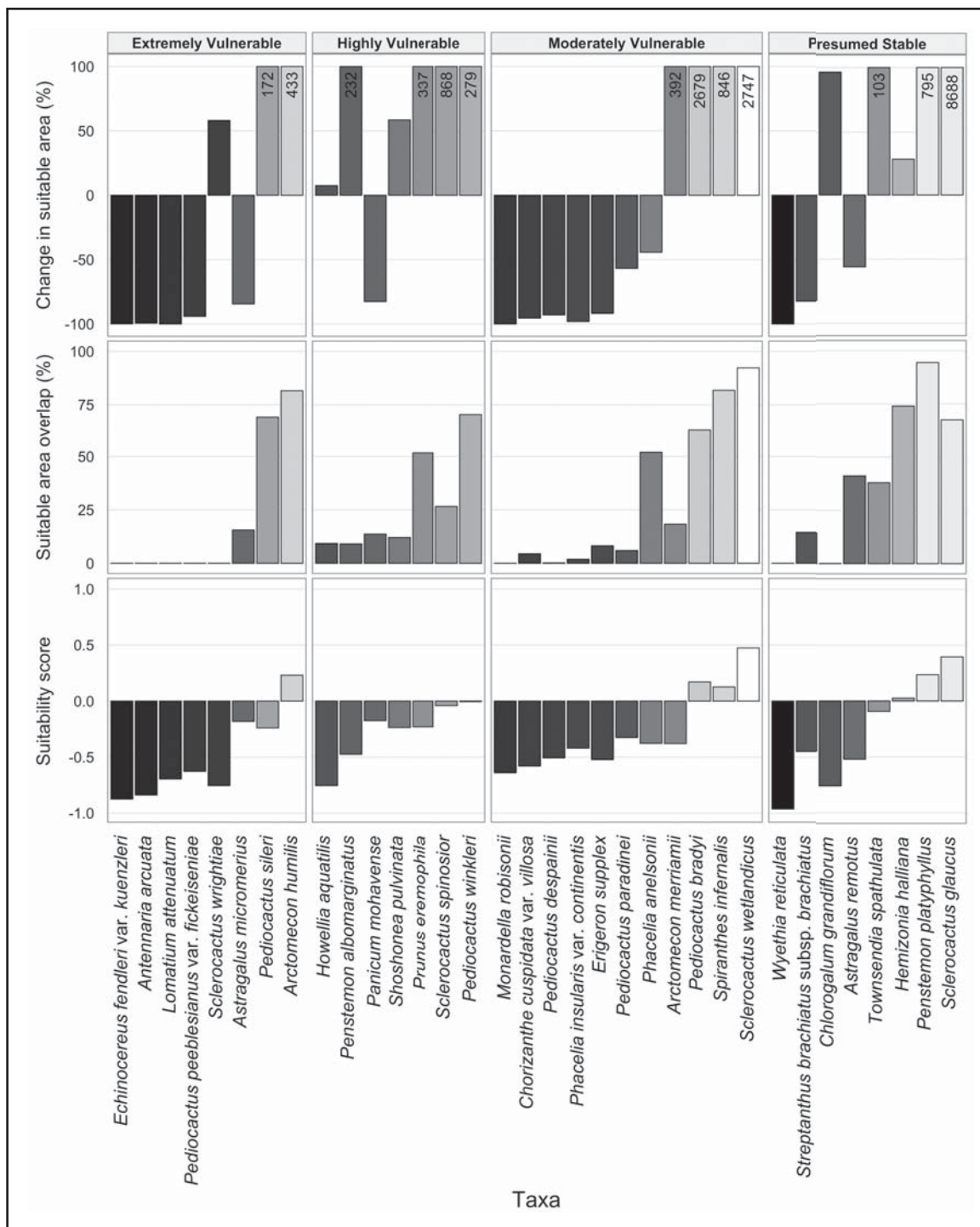


Figure 1. Results of the Species Distribution Modeling (SDM) measures (y-axes) displayed by the Climate Change Vulnerability Index (CCVI) scores (columns). Shading indicates vulnerability calculated by SDM. Darker shading indicates increased vulnerability. Change in suitable area values greater than the positive y-axis limit (100%) is provided in the bar.

climate change because of possible future phenological mismatches between plant species and pollinators due to climate-induced changes in timing of flowering and/or pollinator emergence (Gilman et al. 2012). Given the small percentage of its present suitable area predicted to remain

suitable by midcentury, the tiny fraction of overlap between the predicted future and present suitable areas, potential stochastic loss of small, disjunct populations, and the multiple limiting life history traits, *P. peeblesianus* subsp. *fickeiseniorum* is facing a cascade of threats and will likely not

be sufficiently protected in the long term by the Critical Habitat that was recently designated (USFWS 2013a). This taxon will require protection in its present and predicted future locations. We recommend monitoring current populations, surveying for new populations, ex situ conservation

Table 4. Results of Species Distribution Modeling (SDM) and Climate Change Vulnerability Index (CCVI) assessments of 34 taxa. CCVI scores (calculated with exposure data): Extremely Vulnerable (EV), Highly Vulnerable (HV), Moderately Vulnerable (MV), and Presumed Stable (PS).

Taxon	No. of Occ.	% Change in Suit. Area	% Suit. Area Overlap	Suit. Score	SDM Score	CCVI Cat. Score	CCVI Num. Score	CCVI Num. Score No Exposure
<i>Antennaria arcuata</i>	29	-99.4	0	-1.000	0.958	EV	14.3	10.5
<i>Arctomecon humilis</i>	10	432.6	82	0.333	0.325	EV	17.6	13.0
<i>Arctomecon merriamii</i>	152	392.3	18	0.114	0.606	MV	6.0	7.0
<i>Astragalus micromerius</i>	14	-84.4	16	-0.295	0.725	EV	11.8	8.0
<i>Astragalus remotus</i>	17	-56.0	41	-0.491	0.708	PS	2.7	5.5
<i>Chlorogalum grandiflorum</i>	55	96.4	0	-0.996	0.778	PS	3.6	3.0
<i>Chorizanthe cuspidata</i> var. <i>villosa</i>	7	-95.5	5	-0.894	0.874	MV	4.6	7.5
<i>Echinocereus fendleri</i> var. <i>kuenzleri</i>	116	-99.9	0	-1.000	0.968	EV	11.4	10.0
<i>Erigeron supplex</i>	17	-91.8	8	-0.703	0.846	MV	6.1	10.5
<i>Hemizonia halliana</i>	14	29.1	74	0.043	0.437	PS	3.8	6.0
<i>Howellia aquatilis</i>	171	7.5	9	-0.737	0.804	HV	9.5	11.0
<i>Lomatium attenuatum</i>	61	-100.0	0	-1.000	0.924	EV	11.3	7.0
<i>Monardella robinsonii</i>	24	-100.0	0	-1.000	0.910	MV	6.6	9.0
<i>Panicum mohavense</i>	11	-82.6	14	-0.269	0.734	HV	7.5	5.0
<i>Pediocactus bradyi</i>	29	2679.2	62	0.299	0.351	MV	6.6	7.0
<i>Pediocactus despainii</i>	19	-93.0	0	-0.994	0.865	MV	5.3	5.0
<i>Pediocactus paradinei</i>	26	-56.8	6	-0.577	0.785	MV	6.6	7.0
<i>Pediocactus peeblesianus</i> subsp. <i>fickeiseniorum</i>	56	-94.1	0	-1.000	0.896	EV	10.8	9.0
<i>Pediocactus sileri</i>	27	172.2	69	0.033	0.492	EV	12.0	9.0
<i>Pediocactus winkleri</i>	15	279.4	70	0.047	0.443	HV	8.5	6.5
<i>Penstemon albomarginatus</i>	47	231.6	9	-0.609	0.749	HV	8.3	9.0
<i>Penstemon platyphyllus</i>	36	794.6	94	0.922	0.239	PS	-0.7	-0.5
<i>Phacelia anelsonii</i>	15	-44.3	52	-0.347	0.633	MV	5.7	6.5
<i>Phacelia insularis</i> var. <i>continentis</i>	12	-98.1	2	-0.944	0.846	MV	4.5	8.0
<i>Prunus eremophila</i>	14	336.6	52	-0.078	0.561	HV	8.5	9.5
<i>Sclerocactus glaucous</i>	124	8688.4	67	1.000	0.236	PS	4.0	3.0
<i>Sclerocactus spinosior</i>	31	867.9	27	-0.001	0.499	HV	8.4	7.0
<i>Sclerocactus wetlandicus</i>	36	2747.3	92	0.525	0.179	MV	6.7	5.0
<i>Sclerocactus wrightiae</i>	113	58.1	0	-1.000	0.888	EV	15.7	12.0
<i>Shoshonea pulvinata</i>	20	58.5	12	-0.281	0.657	HV	7.6	5.0
<i>Spiranthes infernalis</i>	14	846.5	82	0.578	0.316	MV	4.6	10.0
<i>Streptanthus brachiatus</i> subsp. <i>brachiatus</i>	8	-82.3	14	-0.662	0.797	PS	3.8	9.0
<i>Townsendia spathulata</i>	69	102.7	38	-0.086	0.547	PS	2.3	1.5
<i>Wyethia reticulata</i>	23	-100.0	0	-1.000	0.991	PS	3.1	3.0

via seed banking, and possibly assisted migration in the future.

The CCVI and SDM results can also identify taxa that are not threatened by climate change. Although *Sclerocactus*

glaucus (Figure 2C) is listed as Threatened under the US Endangered Species List (USFWS 2010), both the CCVI and

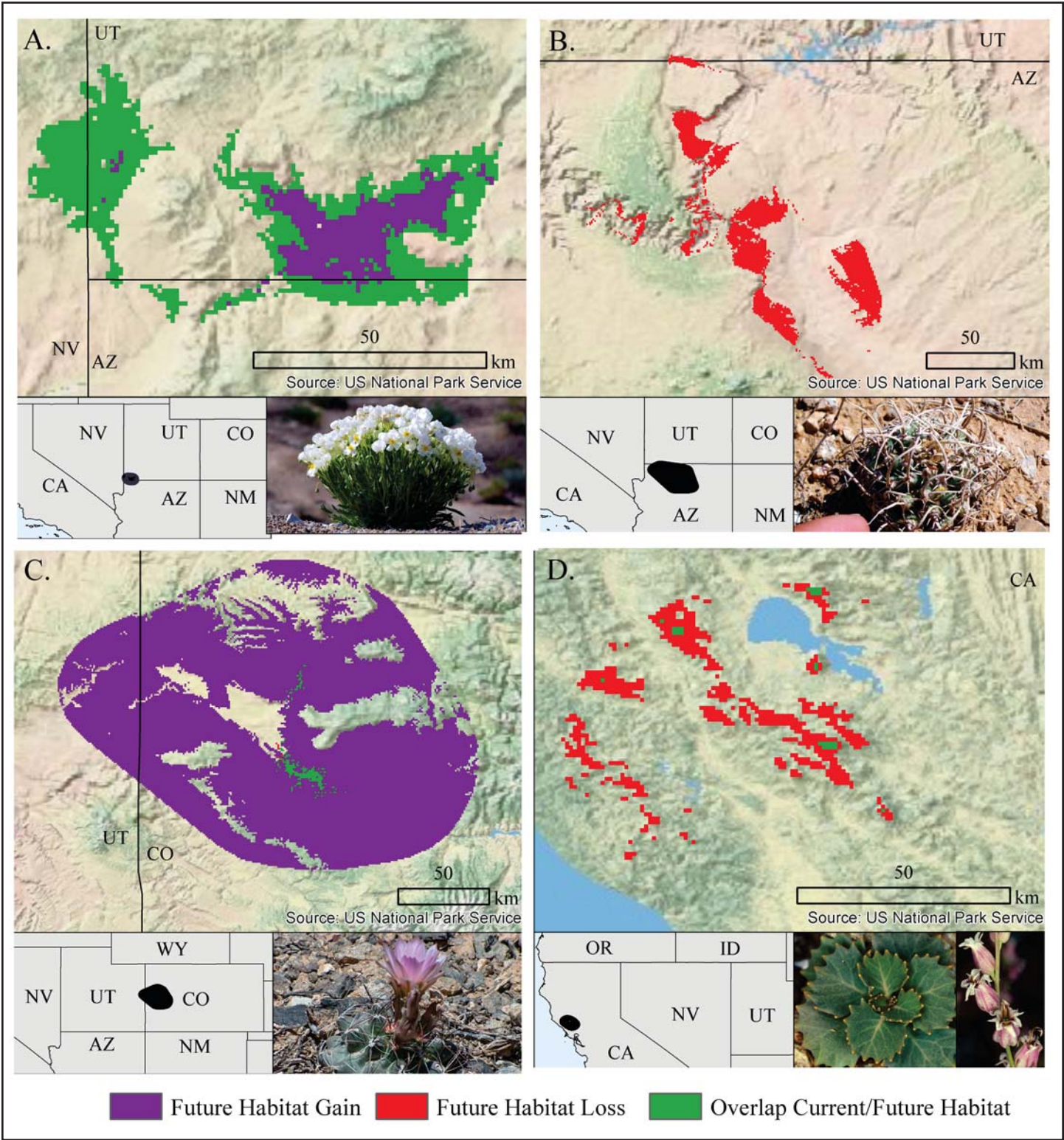


Figure 2. Mean models of 13 climate scenarios for predicted habitat gain (purple), overlap between predicted current and future habitat (green), and predicted habitat loss (red) by midcentury for: (A) *Arctomecon humilis*, (B) *Pediocactus peeblesianus* subsp. *fickeiseniorum*, (C) *Sclerocactus glaucus*, and (D) *Streptanthus brachiatus* subsp. *brachiatus*. Photo credits: (A) Barry C. Johnston and the US Forest Service, (B, C) Shannon Still and Nick Jensen, (D) © Rick York and California Native Plant Society.

SDM predict that *S. glaucus* will not be vulnerable to climate change by midcentury (Figure 1). Endemic to four counties in western Colorado, this small (3–12 cm), globe-shaped cactus is predicted to experience a substantial increase in the size of its suitable area under projected climate conditions by midcentury. With a predicted suitable area overlap of more than 67%, a suitability score of almost 0.4 (Figure 1), and no known limitations to dispersal, *S. glaucus* is predicted to migrate into favorable microhabitats in response to climate change. Therefore, we recommend regularly surveying this species' present and predicted future suitable area to accurately document migration and to protect populations as described in the Recovery Outline (USFWS 2010).

In some cases the CCVI and SDM produce different predictions. *Streptanthus brachiatus* subsp. *brachiatus* is assessed as Presumed Stable using the CCVI score but is predicted to experience a large decrease in both suitable area size and suitability in the future (Figure 2D) leading to a high SDM score (0.797) (Figure 1). Although the CCVI assessment indicates that *S. brachiatus* subsp. *brachiatus* occurs on serpentine barrens (Safford 2005) and that urban development may act as a barrier to dispersal, this taxon occurs in northern California and is not predicted to experience extreme changes in temperature or moisture according to the climate projections available in the ClimateWizard tool (2011a, b). A species with increased sensitivity can still be assessed as Presumed Stable by the CCVI because sensitivity leads to increased vulnerability assessment only if a species is predicted to be exposed to changing climatic conditions. The difference in the conclusions between the CCVI and SDM likely hinge on the different levels of spatial resolution between the climatic data sources used. The resolution of ClimateWizard data used by the CCVI is coarser (~12 km) than the resolution of the SDM climate predictor data presented here (~1 km) such that about 244 SDM cells would fit into one ClimateWizard cell. Finer scale resolution has the ability to capture more local differences when areas are topographically heterogeneous, as is the case in the Coastal Range of California.

When not weighted by exposure, the CCVI score changes from Presumed Stable to Highly Vulnerable, a jump of two vulnerability categories. In all of our examples, using combined vulnerability assessments helps temper the results and shows how the assessments can be influenced by the choice and resolution of climate predictors.

Management Implications of Vulnerability Assessment Results

Using climate change vulnerability assessments in conjunction with other measures of extinction risk like Global Ranks and Red List Assessments greatly improve species conservation efforts. Rare species can have narrow ecological niches, rare habitat types, small populations, restricted geographic ranges (Rabinowitz 1981), and threats other than climate change. Likewise, traditional measures of extinction risk do not consider vulnerability to climate change. Species considered Secure or Apparently Secure from extinction risk (NatureServe G4 and G5 ranks) may be vulnerable to climate change (see Treher et al. 2012 for examples). Results from this study demonstrate that considering climate change impacts may influence conservation prioritization and subsequent management approaches. For example, *Streptanthus brachiatus* subsp. *brachiatus*, which has the highest category of extinction risk (G1), was assessed as not vulnerable to climate change according to the CCVI score, but was considered highly vulnerable using SDM.

While existing conservation plans for some rare taxa may be thorough, these plans typically consider current or past threats in a taxon's current or historic range, but omit future threats. Considering threats from climate change in a taxon's current and future range may require different management strategies and the inclusion of new landowners and stakeholders to protect a taxon from extinction. In addition, targeted and increased frequency of monitoring might be necessary to detect the changes in distribution. For example, it may be necessary to monitor for population and environmental changes at the leading and trailing edges of the range as

suggested for *Pediocactus sileri* (Havens et al. 2015, this issue). Land managers should consider using climate change vulnerability assessments in addition to current conservation status to prioritize species for management.

Limitations of Vulnerability Assessments

Recognizing the limitations of each of these two vulnerability assessment methods is an important step in developing management plans to conserve rare plant taxa. The biggest challenge in assessing plant species is the lack of available occurrence and life history data. Modeling rare species can be difficult because SDM results are less reliable for species with few populations (Elith et al. 2006; Hernandez et al. 2006; Wisz et al. 2008). Three species in our study (*Astragalus micromerius*, *Panicum mojavense*, and *Phacelia anelsonii*) had cAUC values (an indication of model fit) less than 0.7. The low cAUC values indicate that the models are less robust and not much better than random (0.5). All three species were modeled using between 8 and 11 occurrences, so the SDM results for these species are less certain. Land managers should be aware that a low score for model evaluation indicates a less reliable model, and in these cases, the CCVI may provide more information. While there is no set number for minimum number of occurrences used in modeling, it is good practice to use caution when modeling with fewer than 25 occurrences, as model variation is greater (Hernandez et al. 2006). With fewer than 10 occurrences, SDM should be considered as supporting evidence rather than as the primary vulnerability assessment.

Conducting and interpreting species distribution models requires a clear understanding of the assumptions and limitations in the methods. Selecting different input data for modeling, including environmental variables, global circulation models, emission scenarios, and threshold methods can result in drastically different predictions for some taxa, especially those with few occurrences. For example, some models may predict a 100% increase in suitable

area while another model may predict a 50% loss in suitable area for the same taxon. Using the appropriate variables and running different combinations of climate models, predictor variables, and model algorithms can help decrease the uncertainty of an assessment.

The biggest challenge when using the CCVI or other trait-based assessments of climate change vulnerability is the lack of available information to evaluate life history characteristics (Garcia et al. 2014). Species-specific research on pollinators and dispersal mechanism are not commonly available and are frequently inferred based on closely related species and floral and fruit morphology. In this study, only 16 of 34 taxa had information on genetic variability and only one taxon had information on phenological responses to changes in the environment. Additionally, in an assessment of western US plants, only 73 out of 391 taxa had sufficient information on genetic variability, and a mere 13 of 391 taxa had sufficient information on phenology to assign scores to the related factors (Treher et al. 2012). The availability of life history and spatial information varies considerably among taxonomic groups. For example, range maps and life history information are readily available for most birds and mammals in the world. However, only a small fraction of plants worldwide have been thoroughly assessed and even fewer have digitized range maps available. Life history information is not only necessary for robust CCVI assessments, but is also essential to the interpretation of modeling results and subsequent conservation measures. Knowing specific tolerance levels across abiotic and biotic traits can help tailor modeling parameters to each species.

CONCLUSIONS

The results of the CCVI and SDM can enhance the climate adaptation planning process and efforts to develop management strategies to prevent the loss of biodiversity as a result of climate change (Cross et al. 2012). For example, land managers can target vulnerable species and geographic areas for seed banking and for more in-

tensive monitoring. Managers could also attempt to minimize non-climate related threats to vulnerable populations, such as invasive species, in an attempt to make the populations more robust and resilient to climate change. If necessary, land managers could consider assisted migration using SDM to guide placement of new populations in more suitable areas. While the two methods for vulnerability assessment can support and complement each other, in some cases one method reveals vulnerability or sensitivity where the other does not. The SDM can detect finer level changes in climatic requirements that the CCVI is unable to detect. Likewise, the CCVI can reveal life history traits that could limit the species' adaptive capacity to migrate and persist in the SDM's predicted suitable area. While neither the CCVI nor SDM can assess the vulnerability of all species in all situations, using the two approaches in combination provides complementary results by evaluating different measures of climate vulnerability. The combined results can be used to improve decision-making for managing species of concern.

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Appendix 1. Global circulation model and emission scenario combinations used in SDM analyses.

A2A models: CCCMA CGCM2, CSIRO Mk2, HCCPR HADCM3, NIES99

B2A models: CCCMA CGCM2, CSIRO Mk2, HCCPR HADCM3, NIES99

A1B models: CCCMA CGCM3.1, CSIRO Mk3.0, BCCR BCM2.0, INM CM3.0, MIROC3.2 [medres]

Appendix 2. SDM model fitting results. All numeric values are the average of 13 total models for each species (13 GCM-SRES).

Taxon	Training Occurrences (n)	Testing Occurrences (n)	Training Background Points (n)	Testing Background Points (n)	MaxKappa threshold	AUC	Null AUC (nAUC)	Corrected AUC (cAUC)	Occurrence Testing Points (pwd)	Training Distance (km)	Background (pwd) Test Points (n)	Null Model Training Distance (km)	Model Iterations (n)
<i>Antennaria arcuata</i>	22	7	7520	2500	0.834	0.877	0.501	0.876	7	30.6	14	30.6	338
<i>Arctomecon humilis</i>	8	2	5324	1772	0.619	0.921	0.45	0.921	2	5.1	4	5.1	64
<i>Arctomecon merriamii</i>	114	38	7607	2500	0.659	0.746	0.508	0.738	36.4	4	71.8	4	682
<i>Astragalus micromerius</i>	10	4	7510	2500	0.499	0.642	0.513	0.629	4	22.9	8	22.9	68
<i>Astragalus remotus</i>	13	4	6300	2096	0.542	0.747	0.519	0.728	4	3.7	8	3.7	94
<i>Chlorogalum grandiflorum</i>	41	14	7540	2500	0.658	0.864	0.502	0.862	14	3	28	3	250
<i>Chorizanthe cuspidata</i> var. <i>villosa</i>	7	1.6	3694	1228	0.669	0.972	0.475	0.972	2	3.5	4	3.5	102
<i>Echinocereus fendleri</i> var. <i>kuenzleri</i>	87	29	7580	2500	0.711	0.911	0.526	0.885	26.9	1.4	51	1.4	608
<i>Erigeron supplex</i>	16	4.2	7467	2485	0.669	0.986	0.496	0.986	5	8	10	7.9	196
<i>Hemizonia halliana</i>	10	4	7509	2500	0.610	0.794	0.516	0.778	4	9.8	8	9.8	110
<i>Howellia aquatilis</i>	128	43	7628	2500	0.530	0.980	0.586	0.894	17.9	10.2	27.2	13.3	1450
<i>Lomatium attenuatum</i>	46	15	7544	2500	0.764	0.854	0.527	0.827	12.8	4.2	24.3	4.4	458
<i>Monardella robinsonii</i>	18	6	7516	2500	0.778	0.949	0.492	0.949	6	5.4	12	5.4	194
<i>Panicum mohavense</i>	8	3	7505	2500	0.524	0.611	0.483	0.611	3	9.9	6	9.9	60
<i>Pediocactus bradyi</i>	22	7	6744	2241	0.783	0.942	0.496	0.942	7	2.7	14	2.7	436
<i>Pediocactus despainii</i>	14	5	7510	2500	0.596	0.803	0.474	0.803	5	6.2	10	6.1	144
<i>Pediocactus paradinei</i>	20	6	5464	1815	0.787	0.964	0.493	0.964	6	2	12	2	308
<i>Pediocactus peeblesianus</i> subsp. <i>fickeiseniorum</i>	42	14	7535	2500	0.655	0.769	0.500	0.769	14	5.3	28	5.3	284
<i>Pediocactus sileri</i>	20	7	7517	2500	0.618	0.791	0.490	0.791	7	5.9	14	5.9	158
<i>Pediocactus winkleri</i>	11	4	7508	2500	0.645	0.838	0.466	0.838	4	6.2	8	6.2	130
<i>Penstemon albomarginatus</i>	35	12	7534	2500	0.830	0.928	0.499	0.928	12	5.1	24	5.1	532
<i>Penstemon platyphyllus</i>	27	9	7527	2500	0.740	0.941	0.500	0.941	9	7.1	18	7.1	378
<i>Phacelia anelsonii</i>	11	4	7511	2500	0.501	0.673	0.516	0.657	4	26	8	26	104
<i>Phacelia insularis</i> var. <i>continentis</i>	10	3.1	7470	2489	0.738	0.965	0.481	0.965	4	3.6	8	3.6	90
<i>Prunus eremophila</i>	10	4	4381	1457	0.612	0.951	0.488	0.951	4	1.4	8	1.4	148
<i>Sclerocactus glaucous</i>	93	31	7585	2500	0.741	0.930	0.505	0.925	29.8	2.7	59.1	2.7	842
<i>Sclerocactus spinosior</i>	23	8	7522	2500	0.667	0.740	0.502	0.738	8	17.5	16	17.5	198
<i>Sclerocactus wetlandicus</i>	27	9	7519	2500	0.765	0.884	0.498	0.884	9	5.3	18	5.3	332
<i>Sclerocactus wrightiae</i>	85	28	7563	2500	0.592	0.920	0.499	0.920	27.6	3.1	55.2	3.1	288
<i>Shoshonea pulvinata</i>	15	5	7515	2500	0.821	0.934	0.508	0.926	5	14.1	9.9	14.3	358
<i>Spiranthes infernalis</i>	10	4	4359	1452	0.607	0.899	0.488	0.899	4	1.3	8	1.3	192
<i>Streptanthus brachiatus</i> subsp. <i>brachiatus</i>	6	2	5259	1751	0.620	0.933	0.475	0.933	2	1.8	4	1.8	64
<i>Townsendia spathulata</i>	52	17	7552	2500	0.731	0.786	0.556	0.730	15.6	11.8	26.9	13.4	326
<i>Wyethia reticulata</i>	17	6	4381	1455	0.769	0.968	0.526	0.941	6	1.3	12	1.3	338

Appendix 3. Mean \pm standard deviation for the individual and combined Species Distribution Modeling values as classified by Global Rank, Climate Change Vulnerability Index scores unweighted by climate exposure (CCVI unwt), weighted by climate exposure (CCVI wtd), and by Endangered Species Act Status (listed as Threatened, Endangered, or unlisted).

		No.	Suitable Area	Suitable Area Overlap	Suitability Score	SDM Score
Global Rank	G1	8	494.7 \pm 946.2	37.49 \pm 35.70	-0.221 \pm 0.380	0.619 \pm 0.263
	G2	15	686.1 \pm 2236.1	30.78 \pm 32.88	-0.326 \pm 0.382	0.669 \pm 0.244
	G3	11	290.3 \pm 828.5	23.18 \pm 31.08	-0.395 \pm 0.394	0.689 \pm 0.237
CCVI unwt	EV	7	150.5 \pm 359.8	25.85 \pm 38.36	-0.483 \pm 0.467	0.729 \pm 0.285
	HV	14	283.5 \pm 745.3	19.99 \pm 23.86	-0.365 \pm 0.245	0.715 \pm 0.183
	MV	8	354.8 \pm 974.2	44.47 \pm 33.49	-0.165 \pm 0.330	0.582 \pm 0.217
	PS	5	1916.4 \pm 3800.8	39.99 \pm 41.55	-0.237 \pm 0.601	0.558 \pm 0.332
CCVI wtd	EV	8	23.1 \pm 193.3	20.81 \pm 34.30	-0.497 \pm 0.393	0.772 \pm 0.241
	HV	7	242.7 \pm 315.2	27.55 \pm 24.22	-0.274 \pm 0.262	0.623 \pm 0.179
	MV	11	553.3 \pm 1108.2	29.79 \pm 35.37	-0.271 \pm 0.361	0.672 \pm 0.257
	PS	8	1184.1 \pm 3045.9	41.20 \pm 35.25	-0.266 \pm 0.483	0.592 \pm 0.274
ESA status	listed	11	1343.4 \pm 2658.7	41.17 \pm 38.49	-0.226 \pm 0.501	0.586 \pm 0.300
	unlisted	23	115.9 \pm 318.6	24.51 \pm 28.45	-0.370 \pm 0.307	0.701 \pm 0.199