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ORIGINAL PAPER

Bringing indices of species vulnerability to climate change into geographic space: an assessment across the Coronado national forest

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Abstract Indices that rate the vulnerability of species to climate change in a given area are increasingly used to inform conservation and climate change adaptation strategies. These species vulnerability indices (SVI) are not commonly associated with landscape features that may affect local-scale vulnerability. To do so would increase their utility by allowing managers to examine how the distributions of vulnerable species coincide with environmental features such as topography and land use, and to detect landscape-scale patterns of vulnerability across species. In this study we evaluated 15 animal species that had been scored with the USDA-Forest Service Rocky Mountain Research Station's system for assessing vulnerability of species to climate change. We applied the vulnerability scores to each species' respective habitat models in order to visualize the spatial patterns of cross-species vulnerability across the biologically diverse Coronado national forest, and to identify the considerations of spatially referencing such indices. Across the study extent, cross-species vulnerability was higher in higher-elevation woodlands and lower in desert scrub. The results of spatially referencing SVI scores may vary according to the species examined, the area of interest, the selection of habitat models, and the method by which cross-species vulnerability indices are created. We show that it is simple and constructive to bring species vulnerability indices into geographic space: landscape-scale patterns of vulnerability can be detected, and relevant ecological and socioeconomic contexts can be taken into account, allowing for more robust conservation and management strategies.

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Abbreviations

CSVI	Cross-species vulnerability index
EMA	Ecological management area
HDMS	Arizona natural heritage program: heritage data management system
IPCC	Intergovernmental program on climate change
SAVS	System for assessing vulnerability of species to climate change
SVI	Species vulnerability index
SWReGAP	Southwest regional GAP analysis program
USA	United States of America
USDA-FS	United States Department of Agriculture-Forest Service
USFWS	United States Fish and Wildlife Service
USGS	United States Geological Survey

Introduction

Conservation and resource management agendas throughout the USA and the world are increasingly focused on developing effective responses to the ecological consequences of climate change (Hannah et al. 2002; Pressey et al. 2007; Salazar 2009). One of the effects of climate change that is already occurring and projected to intensify is the reshuffling of ecosystems and biodiversity patterns as plants and animals respond to changes in climatic constraints (Parmesan 2006). Many tools have been developed to predict the effects of projected climate change on plants and animals (Rowland et al. 2010; Thuiller et al. 2008); two common strategies for understanding effects of climate change on biodiversity are the assessment of sensitivity and exposure of one or more species to climate change-related effects, and the prediction of changes in species' distributions under changing climate.

Methods to predict species range changes, such as dynamic vegetation models, forest gap models, and species distribution models, have strengths and weaknesses relating to the management objectives, the spatial, temporal and biological scale of the evaluation, and the data available (Thuiller et al. (2008) provides a thorough discussion of different methods to predict species distributions under climate change). Regardless of the specific method, spatial projections of changes in species' distributions have many inherent uncertainties related to the trajectory of future climate, the response of individual species, and unforeseen interactions with other species and landscape features (Heikkinen et al. 2006; Williams and Jackson 2007).

A second strategy for understanding climate change effects on biodiversity is to assess the sensitivity, adaptive capacity and possible exposure, which together define vulnerability, of individual species to the potential effects of climate change (Williams et al. 2008). Species vulnerability indices (SVIs) have been developed by governmental and nongovernmental agencies, including NatureServe (Young et al. 2009) and the USDA-FS (Bagne et al. 2011), that leverage information about aspects of ecology that are believed to be predictive of species' sensitivity, adaptive capacity and exposure to climate change. These tools are used to make rapid assessments about species vulnerability to projected climate change. SVIs are typically made up of sets of questions regarding species' tolerances and life history traits, and their outputs are relative numerical scores of vulnerability given a specified geographic boundary (e.g. a management area, or the species' known range). Although SVI scores are generated based on analysis of vulnerability at a given location, the results of such analyses do not provide information about correlations between scores and landscape features that may be associated with high vulnerability, such as land use or topography.

Applying SVIs to geographic space can provide two key pieces of information that would increase the utility of the scores. First, bringing SVI scores into geographic space allows researchers and managers to explicitly account for the ecological and socioeconomic contexts, such as land use history and ownership boundaries, that complicate the ability of species to respond to changes in their environment. The second benefit to bringing SVIs into geographic space is that the vulnerability scores of all species can be visualized relative to each species' known distributions, so that larger landscape-scale patterns of vulnerability can be detected. This could include the estimation of what we refer to here as "landscape vulnerability", based on combining the vulnerability patterns of the assessed species. Thus "spatializing" SVI scores is a sensible next step for this tool's use. Toward this end, our goal was to demonstrate the utility of bringing SVI scores into space. First, we applied SVI scores from a pilot version of the system for assessing vulnerability of species to climate change (SAVS), developed by the USDA-FS (Bagne et al. 2011; Coe et al. 2011) to spatially explicit habitat models, and examined the spatial patterns of the spatialized SVI. Then we created a cross-species vulnerability map, and, using this map, examined the spatial patterns of the vulnerability of all species assessed with respect to other environmental attributes. As a final step, we identified important considerations for placing SVI scores in geographic context, to further assist managers in prioritizing strategies for managing species.

Methods

Study site

We focused our study on the southwestern USA's Coronado national forest ("Coronado"), which comprises 12 isolated, mountainous ecological management areas (EMAs) in southeastern Arizona and southwestern New Mexico (Fig. 1). Spanning the boundaries connecting the Rocky Mountains, the Sierra Madre, and the Sonoran and Chihuahuan desert biomes, and reaching from 1038 to 2831 m in elevation, the Coronado's "sky island" mountain ranges number among the most biologically diverse landscapes in the world (Marshall 1957; Myers et al. 2000). Climate change adaptation planning is critical to managing this landscape as it is projected to become both warmer and drier with climate change, exacerbating many issues in what is already a water-limited region (IPCC 2007; Seager et al. 2007).

Species data

We analyzed a subset of mammal, bird, reptile and amphibian species identified by biologists from the Coronado as being of management concern—either listed with the USFWS (as Threatened, Endangered, Candidate, Of Concern or Under Review), or with the USDA-FS (as Management Indicator Species, Species of Interest or Sensitive) (Coe et al. 2011). Each species was scored for its vulnerability to climate change by biologists at

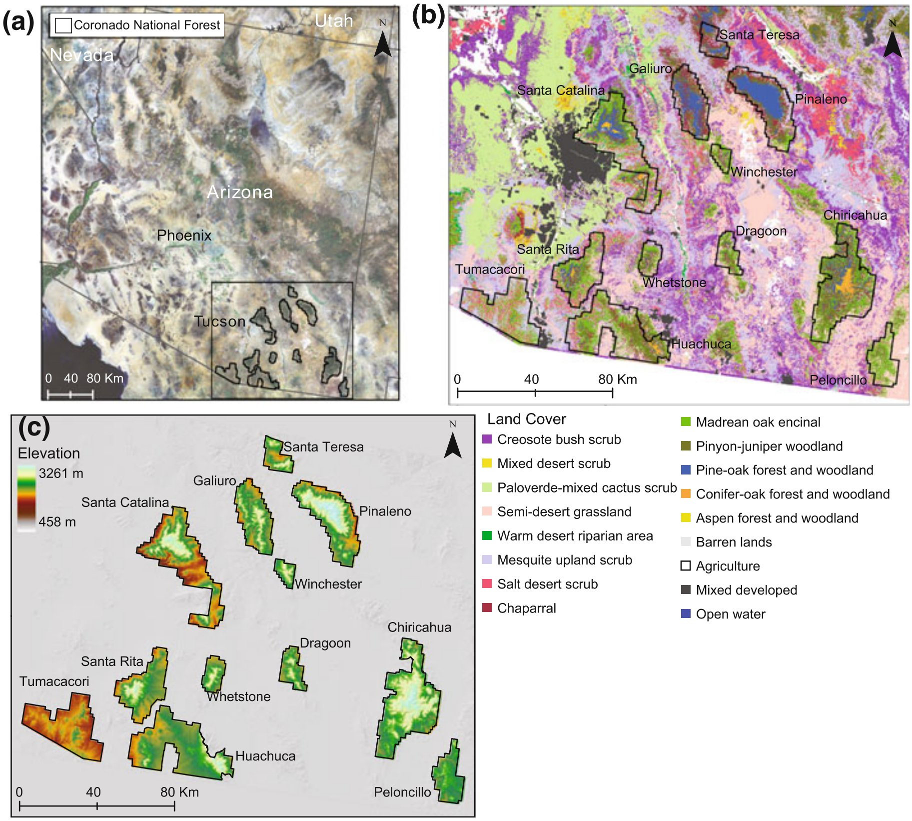


Fig. 1 **a** The study site was the Coronado national forest, located in southeastern Arizona and southwestern New Mexico. **b** The Coronado encompasses over 10 separate mountain ranges across multiple land cover types. **c** These ecosystem patterns are largely the result of elevation-driven climate gradients

the USDA-FS' Rocky Mountain Research Station, as part of a separate study (Coe et al. 2011), using a pilot version of their SAVS assessment tool (Bagne et al. 2011). The SAVS tool is a questionnaire with multiple-choice responses, each of which is associated with a point value. Those points are then used to calculate vulnerability scores. The USDA-FS researchers examined published literature detailing species' ecology, expected habitat changes, and output from a vegetation model that predicts potential future locations of suitable climate to support dominant vegetation communities, to answer the questions and thus estimate the relative vulnerability of a species to climate change within the Coronado national forest (Coe et al. 2011). SAVS output is an overall numerical vulnerability score ranging from -20 to $+20$. It also provides four categorical scores that represent species' sensitivity and exposure to climate change in the categories of habitat, physiology, phenology and biotic interactions (Fig. 2). Each categorical score is calculated from a unique subset and number of the total questions and then scaled to a common range of -5 to $+5$. Notably, categorized scores do not sum to the overall score range, which is based on all 25 questions. Further, a highly vulnerable or resilient score in one category does not in and of itself determine overall vulnerability. Rather, an overall vulnerability score is a function of the total number of questions found to relate to a vulnerability trait and not simply the sum

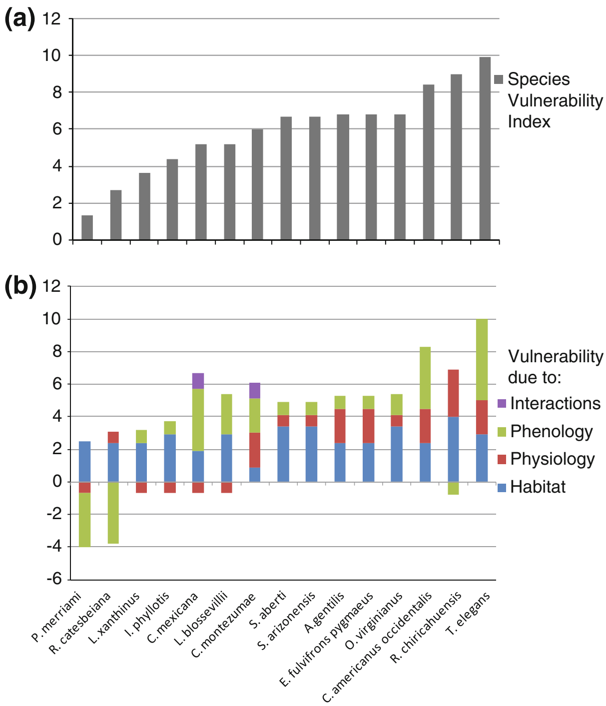


Fig. 2 **a** Species vulnerability scores and **b** the sub-scores for the 15 species examined suggest a wide range of vulnerability across the species of concern in the Coronado. The overall scores are calculated using all questions in the species vulnerability assessment. The sub-scores are calculated using subsets of questions, and scaled to a maximum value of 5 within each category; that results in the categorical scores not being a sum of the overall score

of its vulnerability in one or more categories. Finally, this tool is intended for use with multiple species and provides a measure of relative vulnerability, enabling managers to prioritize conservation practices among the many species of management concern.

To examine the spatial patterns of vulnerable species, we used the USGS' SWReGAP range models, which incorporate known species' occurrence data and correlated environmental factors to map "potential or probable habitat", as a raster image with 30 m spatial resolution (Boykin et al. 2007; SWReGAP 2011). These potential habitat models estimate presence based on the resources and conditions present in areas where a species persists and reproduces or otherwise occurs, and rely on available literature and species occurrence data to generate a spatial representation of habitat within the species known range. These models were subjected to expert review, based on the habitat relationships, the range extent and qualification, and the spatial depiction of the predicted habitat (i.e. the model). These reviews may be found online (SWReGAP 2011). For this project, we analyzed a subset of 15 species from the larger project (Coe et al. 2011) that had SWReGAP habitat models.

We assigned each species' SAVS vulnerability score to each pixel of potential habitat, with non-potential habitat assigned a value of 0. This provided us with a spatial pattern of vulnerability scores (referred to here as SAVS maps). To demonstrate the utility of a cross-species vulnerability index, we overlaid the score-coded habitat maps of the 15 species, summed the vulnerability scores in each pixel, and divided the value by number of species potentially present, to create a mean vulnerability score, what we refer to here as a "cross-species vulnerability index" (CSVI). We interpreted a mean species vulnerability score to represent a prioritization of the landscape for land managers, if all species were managed similarly. We determined that use of the median score or the mode score would lead to masking outliers, which we felt were important to account for in this index. Importantly, the species in this study are not all managed similarly, and we address the implications in our discussion below. The individual species SAVS maps and the CSVI map were used as our response variables in subsequent comparisons to environmental variables.

Environmental data

Examining the vulnerability of a species in the context of land use, land cover and other environmental factors is useful for planning climate change adaptation because a species' vulnerability may be exacerbated or ameliorated based on landscape features within its habitat. We considered six environmental explanatory variables that could potentially affect species adaptation to climate change: elevation, land cover, percent vegetation cover, distance to perennial water sources, distance to roads, trails or recreation sites, and land stewardship category (Table 1; Ernst et al. 2007; LANDFIRE 2008; Lowry et al. 2007; USDA-FS 2009; USGS 2006). We used elevation as a proxy for climatic variables such as temperature and precipitation, because the mountain ranges in the Coronado NF have elevation-based climatic gradients that drive the arrangement of ecosystems along their slopes, with temperature decreasing and precipitation increasing with greater elevation (Davison et al. 2010; Marshall 1957). We used the vector data defining the roads, trails and water sources within the Coronado (USDA-FS 2009) to create raster layers quantifying the nearest distance to perennial streams, lakes or reservoirs, and the nearest distance to roads, trails or recreation sites, per 30-m pixel. Both these rasters showed a left-skewed distribution of values so we used the natural log of these data in analysis, to meet the assumption of normality. We used the SWReGAP land stewardship dataset to account for existing mandates to manage for biodiversity (Ernst et al. 2007). The values range from category 1, meaning the land is mandated for biodiversity management and allowance for natural disturbances, to category 4, meaning that no known mandate for biodiversity management exists. We converted the stewardship data set from a vector format to a raster format to match the other data sets, at 30 m spatial resolution, based on a "majority rule" for each pixel.

Table 1 Sources and details of environmental data we used as explanatory variables in our statistical analyses

Variable	Source	Creation date	Original spatial resolution	Data type	Reference
Elevation	USGS national elevation dataset	2000	30 m	Continuous	USGS (2006)
Land cover	SWReGAP	2001	30 m	Categorical	Lowry et al. (2007)
Percent vegetation cover	LANDFIRE	2000	30 m	Continuous	LANDFIRE (2008)
Distance to perennial water	USDA-FS	2010	(vector)	Continuous	USDA-FS (2009)
Distance to roads, trails and recreation sites	USDA-FS	2010	(vector)	Continuous	USDA-FS (2009)
Land stewardship	SWReGAP	2009	(vector)	Categorical	Ernst et al. (2007)

Data analysis and visualization

We first gathered the mean or the modal values for continuous or categorical environmental variables, respectively, within each species' potential habitat, across EMAs. Then we ran ANOVA or regression analyses to evaluate relationships between SAVS scores and these aggregated environmental variables. Likely due in part to small sample size ($n = 15$ species), relationships between SAVS scores and any of the environmental variables were not significant, and we did not include the results of these analyses in this paper. We then analyzed the CSVI with respect to the six environmental variables. Because we were analyzing spatial patterns across large swaths of land divided into 30-m pixels, our sample size across the study site was over 7 million. Additionally, spatial autocorrelation can affect the Type I error rate, although the effect is negligible in analyses with a large sample size (in this study, $n = 7{,}490{,}500$; Beale et al. 2010). Nonetheless, to reduce the effects of spatial autocorrelation and oversampling, we selected a random 1% of pixels for analysis ($n = 74{,}905$), which leads to an average of 3,000 m between sample units. We also did not include in the ANOVA and Tukey–Kramer statistical tests pixels within this subset that were in land cover types with a sample size of less than $n = 30$. We conducted step-wise multiple regression analysis to examine the relative power of the environmental variables to explain patterns of CSVI, across the study site. We used minimum Bailey's information criterion as the requirement for adding variables to the forward-stepping model, and used Adjusted R^2 as the measure of explanatory power. We then analyzed the effects of land cover on CSVI, using ANOVA and Tukey–Kramer statistical tests to compare the relationships to CSVI among land cover types. We undertook these analyses in MATLAB, ArcGIS, and JMP (ESRI 2010; MathWorks 2010; SAS 2010).

Results

Spatial patterns of individual species vulnerability

Overall SAVS vulnerability scores ranged from 1.3 to 9.9 among the 15 species, with an average of 5.97 (Fig. 2; Table 2). Habitat-based vulnerability ranged from 0.9 to 4.0 (mean = 2.68), physiological vulnerability ranged from −0.7 to 2.9 (mean = 0.85), phenological vulnerability ranged from −3.8 to 5.0 (mean = 1.03), and vulnerability due to biotic interactions ranged from 0.0 to 1.0 (mean = 0.13). Based on the SWReGAP habitat models, the 15 species assessed were mainly associated with mid-elevation habitat types, with a mean elevation of 1697.6 m, and majority land cover most often being Madrean oak encinal (Table 2). The majority SWReGAP stewardship category of habitat for all but two species was of multiple and extractive uses (category 3); *Accipiter gentilis* and *Empidonax fulvifrons pygmaeus* habitats were primarily associated with stewardship category 2, wherein biodiversity is explicitly managed and natural disturbances are suppressed. Average suitable habitat was 594.6 m mean distance from roads, trails or recreation sites, ranging from 78.7 to 693.4 among species. Mean distance to perennial water sources averaged 1676.9 m among species, with a range of 754.8 to 2505.8 m. Potential habitat of *Coccyzus americanus occidentalis* was closest to water sources, and to trails, roads or recreation sites. *A. gentilis* and *E. fulvifrons pygmaeus* had habitat farthest away from water sources (2259.9 and 2505.8 m mean distance, respectively).

Table 2 Animal species evaluated in our study and the mean or majority (modal) values of environmental parameters in their potential habitats, across all EMAs

Common name Latin name	Vulnerability score: (a) Habitat (b) Physiology (c) Phenology (d) Biotic interactions (e) Overall	EMAs with potential species habitat	Mean elevation (m)	Majority land cover	Majority percent cover	Majority steward-ship category	Mean distance to perennial water sources (m)	Mean distance to roads, trails or recreation sites (m)
Northern goshawk *Acipiter gentilis*	(a) 2.4 (b) 2.1 (c) 0.8 (d) 0.0 (e) 6.8	All	2114.61	Pine-oak woodland	80–90%	2	2259.89	625.01
Mexican long-tongued bat *Choeronycteris mexicana*	(a) 1.9 (b) −0.7 (c) 3.8 (d) 1.0 (e) 5.2	All	1685.27	Madrean oak encinal	70–80%	3	1670.57	669.33
Western yellow-billed cuckoo *Coccyzus americanus occidentalis*	(a) 2.4 (b) 2.1 (c) 3.8 (d) 0.0 (e) 8.4	3, 8, 11	1499.04	Riparian woodland	20–30%	3	754.80	78.67
Montezuma quail *Cyrtonyx montezumae*	(a) 0.9 (b) 2.1 (c) 2.1 (d) 1.0 (e) 6.0	All	1647.05	Madrean oak encinal	70–80%	3	1713.91	681.08
Northern buff-breasted flycatcher *Empidonax fulvifrons pygmaeus*	(a) 2.4 (b) 2.1 (c) 0.8 (d) 0.0 (e) 6.8	2, 3, 5, 7, 8, 9, 10	2041.47	Pinyon-juniper woodland	70–80%	2	2505.80	602.39
Allen's lappet brown bat *Idionycteris phyllotis*	(a) 2.9 (b)−0.7 (c) 0.8 (d) 0.0 (e) 4.4	2, 7, 8, 9, 11, 12, 13	1863.88	Madrean oak encinal	60–70%	3	1833.69	630.00
Western red bat *Lasiurus blossevillii*	(a) 2.9 (b) −0.7 (c) 2.5 (d) 0.0 (e) 5.2	All	1563.64	Madrean oak encinal	50–60%	3	1544.10	693.36
Western yellow bat *Lasiurus xanthinus*	(a) 2.4 (b) −0.7 (c) 0.8 (d) 0.0 (e) 3.6	All	1528.50	Madrean oak encinal	70–80%	3	1461.55	673.71
White-tail deer *Odocoileus virginianus*	(a) 3.4 (b) 0.7 (c) 1.3 (d) 0.0 (e) 6.8	All	1711.62	Madrean oak encinal	70–80%	3	1772.19	674.38
Merriam's mesquite mouse *Peromyscus merriami*	(a) 2.5 (b) −0.7 (c) −3.3 (d) 0.0 (e) 1.3	4, 6, 10, 12	1137.09	Mesquite upland scrub	30–40%	3	1219.94	491.01
American bullfrog *Rana catesbeiana*	(a) 2.4 (b) 0.7 (c) −3.8 (d) 0.0 (e) 2.7	3, 4, 8, 10, 11	1540.32	Riparian woodland	60–70%	3	1051.58	624.64
Chiricahua leopard frog *Rana chiricahuensis*	(a) 4.0 (b) 2.9 (c) −0.8 (d) 0.0 (e) 9.0	All	1683.93	Madrean oak encinal	80–90%	3	1599.89	525.36

Table 2 continued

Common name Latin name	Vulnerability score: (a) Habitat (b) Physiology (c) Phenology (d) Biotic interactions (e) Overall	EMAs with potential species habitat	Mean elevation (m)	Majority land cover	Majority percent cover	Majority steward-ship category	Mean distance to perennial water sources (m)	Mean distance to roads, trails or recreation sites (m)
Abert's squirrel *Sciurus aberti*	(a) 3.4 (b) 0.7 (c) 0.8 (d) 0.0 (e) 6.7	3, 4, 5, 6, 9, 10, 11, 12, 13	1699.21	Madrean oak encinal	50–60%	3	2108.78	662.97
Arizona gray squirrel *Sciurus arizonensis*	(a) 3.4 (b) 0.7 (c) 0.8 (d) 0.0 (e) 6.7	All	2040.93	Pine-oak woodland	80–90%	3	1840.78	627.82
Elegant trogon *Trogon elegans*	(a) 2.9 (b) 2.1 (c) 5.0 (d) 0.0 (e) 9.9	All except 13	1760.23	Madrean oak encinal	50–60%	3	1816.59	658.67

EMAs are as follows: *2* Peloncillo, *3* Huachuca, *4* Tumacacori, *5* Whetstone, *6* Santa Rita, *7* Dragoon, *8* Chiricahua, *9* Winchester, *10* Santa Catalina, *11* Pinaleno, *12* Galiuro, *13* Santa Teresa

Spatial patterns of the CSVI

Across the Coronado, cross-species vulnerability to climate change ranged from 2.5 to 9.0 (mean = 5.78). Visual examination showed the CSVI to be higher with higher elevations (seen qualitatively in Fig. 3), where lower temperatures and greater precipitation is found (Davison et al. 2010). Stepwise multiple linear regression showed land cover to explain nearly 80% of the variation in CSVI (Adjusted $R^2 = 0.7900$ when all land cover types were included in the model; $P < 0.0001$). Analysis by ANOVA confirmed that variation in CSVI was significantly related to land cover ($F = 11287.63$, Adusted $R^2 = 0.7904$, $P < 0.0001$, $n = 74{,}905$). Elevation explained an additional 2% of variation (Adjusted $R^2 = 0.8136$ when land cover and elevation were included in the model; $P < 0.0001$) and EMA explained less than 1% of variation (Adjusted $R^2 = 0.8188$ when land cover, elevation and EMA were included in the model; $P < 0.0001$). The rest of the seven explanatory variables provided less than .05% explanatory power.

Tukey–Kramer comparison of CSVI by land cover type grouped CSVI into 10 levels based on CSVI ($q = 3.59$ at $\alpha = 0.05$, $n = 74{,}869$) (Fig. 4). Five land cover types were significantly associated with the highest CSVI: Chihuahuan succulent desert scrub, Mogollon chaparral, North American warm desert bedrock cliff and outcrop, Colorado plateau mixed bedrock canyon and tableland, and Rocky Mountain aspen forest and woodland. Sonoran paloverde-mixed cacti desert scrub and North American warm desert volcanic rockland were significantly associated with the lowest CSVI.

Discussion

Species vulnerability indices are one of the many tools used by researchers and land managers to understand potential climate change effects on species. Place-based but not spatially explicit, SVI can provide greater insights into climate change management of landscapes if they are brought into geographic space. Our study finds that, for the 15 species examined across the Coronado, higher vulnerability is associated with specific land cover types, including rocky or barren land cover, woodlands, and riparian areas (Fig. 4).

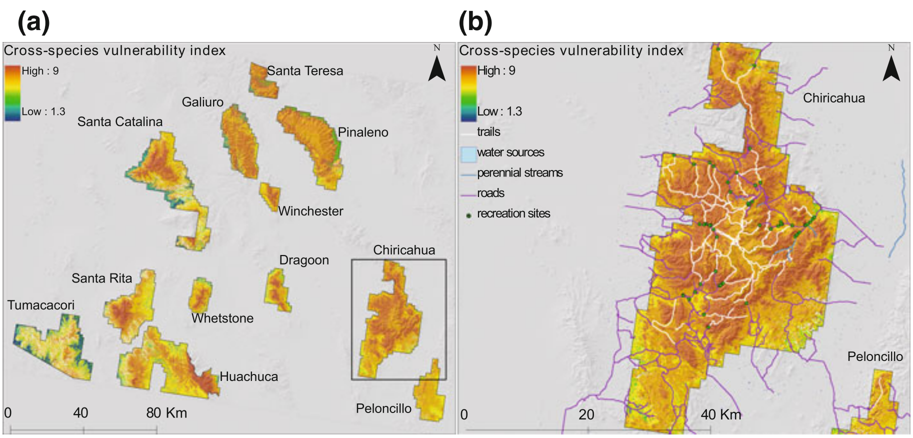
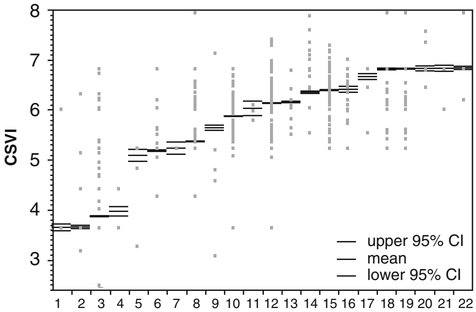


Fig. 3 **a** The cross-species vulnerability index (CSVI). This index shows strong patterns with relation to elevation, both within and across EMAs (refer to Fig. 1 for elevation profile). **b** Landscape-scale examination of these patterns in the context of land use features can inform management decisions within each EMA



Land Cover	Mean	Std Dev	SEM	Lower 95% CI	Upper 95% CI	Level	n
1. N. American Warm Desert Volcanic Rockland	3.62	0.203	0.017	3.58	3.65	A	137
2. Sonoran Paloverde-Mixed Cacti Desert Scrub	3.63	0.205	0.009	3.61	3.64	A	576
3. Apacherian-Chihuahuan Mesquite Upland Scrub	3.84	0.827	0.010	3.82	3.86	B	6518
4. Sonoran Mid-Elevation Desert Scrub	3.94	0.398	0.047	3.84	4.03	B	71
5. N. American Warm Desert Wash	5.06	0.329	0.050	4.96	5.16	C	44
6. Chihuahuan Creosotebush, Mixed Desert and Thorn Scrub	5.15	0.242	0.005	5.14	5.16	C	2666
7. Chihuahuan Sandy Plains Semi-Desert Grassland	5.20	0.000	0.000	5.20	5.20	C,D	42
8. Apacherian-Chihuahuan Piedmont Semi-Desert Grassland and Steppe	5.34	0.350	0.003	5.33	5.34	D	10,334
9. N. American Warm Desert Riparian Mesquite Bosque	5.61	0.857	0.056	5.50	5.72	E	233
10. Madrean Encinal	5.84	0.348	0.003	5.83	5.84	F	19,204
11. N. American Warm Desert Riparian Woodland and Shrubland	5.99	0.092	0.017	5.96	6.03	F, G	30
12. Madrean Pinyon-Juniper Woodland	6.10	0.435	0.004	6.09	6.11	G	14,197
13. Rocky Mountain Ponderosa Pine Woodland	6.12	0.175	0.003	6.12	6.13	G	2990
14. Madrean Upper Montane Conifer-Oak Forest and Woodland	6.32	0.420	0.012	6.29	6.34	H	1178
15. Madrean Pine-Oak Forest and Woodland	6.36	0.302	0.004	6.35	6.37	H	6267
16. N. American Warm Desert Lower Montane Riparian Woodland	6.38	0.353	0.027	6.32	6.43	H	177
17. Madrean Juniper Savanna	6.63	0.229	0.017	6.60	6.66	I	182
18. N. American Warm Desert Bedrock Cliff and Outcrop	6.78	0.151	0.003	6.77	6.79	J	2070
19. Mogollon Chaparral	6.79	0.140	0.002	6.78	6.79	J	6908
20. Rocky Mountain Aspen Forest and Woodland	6.79	0.076	0.005	6.78	6.80	J	256
21. Chihuahuan Succulent Desert Scrub	6.80	0.063	0.005	6.79	6.80	J	172
22. Colorado Plateau Mixed Bedrock Canyon and Tableland	6.80	0.085	0.003	6.80	6.81	J	617

Fig. 4 Variation explained in the CSVI by land cover (ANOVA: $F = 11287.63$, adusted $R^2 = 0.7904$, $P < 0.0001$, $n = 74{,}905$) suggests that there are significant differences in CSVI among land cover types, including higher CSVI in woodlands and lower CSVI in desert scrub lands (Tukey–Kramer: $q = 3.59$ at $\alpha = 0.05$). *SEM* standard error of the mean

Considerations for creating a climate change vulnerability index across species

Examining the habitat of a single vulnerable species in the context of land use, land cover and other environmental factors is useful for planning climate change adaptation for that one species, because a species' vulnerability may be exacerbated or ameliorated based on landscape features within its habitat. To leverage SVI further, a CSVI can aid managers in identifying areas that have a consistently high vulnerability score across a suite of species. In our analysis we identified four factors to consider when bringing SVIs into geographic space and comparing them against environmental parameters. The choice of species, management area, habitat model, and cross-species index algorithm all affect the results and interpretation of cross-species vulnerability across a landscape.

Species assessed

In creating a geographically explicit vulnerability index that aggregates the scores of individual species with the intent of examining landscape-scale vulnerability patterns, careful consideration should be given to how many species are included, where the species

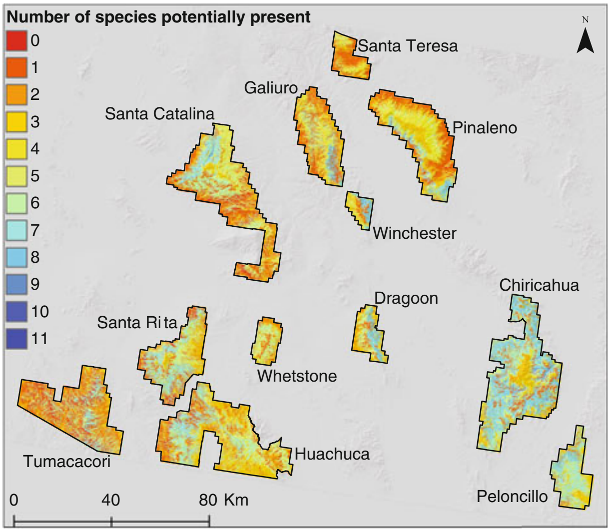


Fig. 5 Number of species potentially present in the Coronado was calculated based on overlaying habitat models. The highest potential species presence in this study falls at mid-elevations, whereas the lower elevations and higher elevations tend to have fewer species potentially present

are found within the study extent, and their reasons for evaluation. In our study, 15 species were examined spatially. Because of the steep, climatically driven biological gradients that the Coronado comprises, the biodiversity in this forest is very high (Marshall 1957). Given that we select a certain quantity of species that together span all of the ecosystems across the study extent, species habitats will likely overlap less in these steep gradients than if we were to analyze the same quantity of species in a site with fewer ecosystems. This is a mixed blessing; we get to examine species vulnerability across many ecosystems, but we require analysis of a higher amount of species in order to gain a robust measure of cross-species vulnerability. Across our study site, the mean potential presence of species was four species per 30-m pixel, with the highest mean potential species presence in the Chiricahua EMA (5.4 species potentially present on average) and the lowest mean potential species presence in the Santa Teresa EMA (2.6) (Fig. 5). The habitat models of *Rana chiricahuensis*, *R. catesbeiana*, *C. americanus occidentalis* and *E. fulvifrons pygmaeus* showed little potential presence in the Coronado. Many of the species examined in our study were present in one half of the region, e.g. the eastern (e.g. *Idionycteris phyllotis*) western (e.g. *Peromyscus merriami*) or southern (e.g. *Trogon elegans*) ranges, consequent to the intersection of major biomes in this area (Marshall 1957). Additionally, habitat models for 10 of the 15 species analyzed had mean potential presence between 1,400 and 1,800 m (Table 1). Accordingly, areas of the study extent that had potential presence of species $\geq$7 were concentrated in elevations between 1,370 and 2,224 m, whereas the higher-elevation tips and the lower-elevation rings of each EMA tended to have $\leq$3 species potentially present (Fig. 5). As a result of the diversity of species ranges, the CSVI was often based on six or fewer scores—particularly at the lowest and highest elevations of the study extent—leading to potential bias, e.g. where one species VI score was substantially greater or less than the other few in the same pixel. For example, the low CSVI scores at the bottom of the Santa Catalina and Tumacacori EMAs is driven largely by the potential presence of *P. merriami* (the low CSVI can be seen in Fig. 4a). Analysis of more species, especially those with habitats in the lower and higher elevations of these gradients, as habitat models become available for those species of concern in the Coronado, will reduce this type of bias and make the CSVI an even stronger tool for understanding landscape-scale species vulnerability patterns.

There can also be issues of interpretation that develop when species that managers want to conserve are included in the same analysis as species that managers would like to eliminate from the lands they manage. In this assessment, *R. chiricahuensis* and *R. catesbeiana* were broadly sympatric; in addition, the former, a federally listed endangered species, was found to be extremely vulnerable to climate change and the latter, an invasive non-native species, was found to be relatively invulnerable (Table 2). The use of the CSVI to make decisions on landscape-scale conservation or management actions is in this instance complicated by the overlap in the habitats that contain species that managers want to manage very differently. A next step for CSVI maps might be to develop separate CSVI for species that are grouped based on how managers may wish to manage them, e.g. different guilds, species that are also threatened by non-climate factors, or invasive non-native species.

Management area of interest

The spatial scale of the CSVI, in consideration of the species ranges and environmental features in and around the study extent, may affect the applicability of a CSVI. In our study area, the habitat models of all 15 species show potential presence both inside and outside of the management boundaries, and animal movement is a key issue that is affected by climate change (Thuiller et al. 2008). For example, in the Huachuca EMA the eastern-most edge of the Huachuca Mountains are partially owned by the Department of Defense. The CSVI was highest in this area of the Huachuca EMA (Fig. 4); collaborative management might be necessary for adaptation of the vulnerable species in that area. Inclusion of a spatial buffer around study sites in both calculating the SVI and analyzing the cross-species vulnerability patterns might be useful for making decisions about how, and with whom, to collaborate in managing climate-change-vulnerable species.

Habitat models used

The age and quality of the data used to generate species' habitat models and the constraints of the modeling algorithm can introduce biases when these habitat models are incorporated into a cross-species vulnerability measure. For example, the SWReGAP potential habitat models do not provide information on the probability of species occurrence. A probabilistic model would have allowed for a weighting based on the probability of occurrence of each vulnerable species, and would reduce bias in the analysis that is due to mis-estimation of species occurrence, i.e. errors of both commission and omission. For example, in our study, the CSVI on the eastern side of the Santa Rita EMA is noticeably lower than at similar elevation but different aspects along the mountain range (Fig. 3a). In this EMA the CSVI is strongly related to the presence of *T. elegans,* with a score of 9.9, the highest score of the species assessed. According to the SWReGAP model there is no potential habitat for *T. elegans* down the eastern slope of the Santa Rita Mountains. However, based on the SWReGAP model's description of the species' habitat, riparian areas supporting *Platanus wrightii*, a tree preferred by *T. elegans*, are located along the east side of the range that is shown not to support *T. elegans* (Boykin et al. 2007). This apparent contradiction is due to the first constraint of the SWReGAP habitat-modeling algorithm: USGS hydrologic unit code boundaries in which an individual was known to have occurred (Boykin et al. 2007). These coarse boundaries constrained *T. elegans'* habitat model boundaries, even though description of the bird's potential habitat suggests otherwise, as does outside evidence of *T. elegans* presence (provided by the Arizona Game and Fish Department's HDMS), found outside those hydrologic units (HDMS 2009). More precise habitat models could lessen these effects; additionally, with a greater number of species evaluated across the study site, these biases might be reduced so that a more robust understanding of landscape-scale cross-species vulnerability could be attained.

Cross-species index creation

We created our CSVI by adding all of the SVI scores together and dividing that sum by the amount of species potentially present, per pixel. This averaging method leads to a CSVI that is specific to the species evaluated and the study site examined. Averaging might be the most useful when assessing a suite of species that have generally overlapping habitats and that are under a similar management strategy (e.g. desire is to increase population levels). An interpolation-based calculation, where a cross-species vulnerability score is estimated between the boundaries of the habitat models, would be a valuable next step for instances where we want to estimate "landscape vulnerability", i.e. the potential vulnerability of species other than those assessed. Alternatively, weighting the SVI scores based on the "value" of each species to the management objectives might be useful; weights might, for example, relate to each species' vulnerability to other factors (e.g. habitat fragmentation).

Beyond the four factors we've identified as important to consider when creating a cross-species index measuring vulnerability to climate change, assumptions and statistical issues including data quality, age, and correlation within and among data sets should be taken into consideration and explicitly acknowledged for the uncertainty that they likely bring to the results. In our study we used interpolated data sets for land cover, percent vegetation cover, and elevation. Each of these has inherent uncertainty in the predictions of its values (LANDFIRE 2008; Lowry et al. 2007; USGS 2006). Additionally, collinearity among the explanatory variables may confound the apparent relationships between each and the CSVI. In our study, vegetation type and elevation were highly correlated ($R^2 = 0.6112$), which was to be expected as elevation drives climate, and climate in turn affects vegetation type. A rule of thumb for using collinear explanatory variables is that they are correlated at less than $R = 0.8$, or $R^2 \leq 0.64$ (Farrar and Glauber 1967), and users should always interpret with prudence analyses of variables that known to be collinear.

Conclusions

Our study demonstrates a method for bringing indices measuring species vulnerability to climate change into geographic space, where the context of land use, land cover and other environmental factors can be more explicitly considered in species-specific plans for adaptation to the effects of climate change. Across the Coronado national forest, the species assessed showed patterns of climate change vulnerability related to specific land cover types, and along the elevation gradients. Particularly in light of the mountainous terrain of the Coronado national forest, prudent management of higher-elevation species is critical, because they may have to contend with both climate change effects and decreasing habitat area as they are forced up the slopes. Future work in spatializing SVI would include evaluation of the vulnerability to climate change of other species in this study site, in order to increase the robustness of the resulting CSVI. Additionally, examination of other management areas and gradients might be useful in providing insight into larger-scale patterns of species vulnerability to climate change. Creation of separate CSVIs for species associated with different types of concerns, e.g. threatened and endangered species, invasive non-native species, and/or economically valuable or intensively managed species, may serve to refine management approaches. Implemented with consideration for the purpose, data sets, and spatial and temporal context relevant to the study, the methodology demonstrated here can bring to light potential management strategies to promote species-scale and landscape-scale adaptation to climate change.

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