Quantifying sensitivity and exposure to climate change in Western North American species

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Abstract

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Significant changes in climate over the coming century will affect different species in different ways. Understanding which species are most vulnerable to climate change is important for guiding conservation efforts and resource management decisions. We present a novel method for assessing vulnerability that quantifies both sensitivity — the degree to which a given change in climate will affect a species — and exposure — how much climate change a species might experience in the near future. We applied our method to 400 species of plants, mammals, birds, and amphibians endemic to Western North America, and compared the results with three other methods that are currently used to assess different aspects of vulnerability. The results suggest certain species might be considerably more vulnerable than we currently recognize. Our method demonstrated robustness against inaccurate distribution data, and consistency across a broad range of spatial scales and different climate datasets. Our metrics also demonstrated the ability to identify vulnerable species while relying on minimal life history information, offering a method to determine which species to prioritize for future conservation actions when faced with a lack of data.

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DEDICATION

— to Gordon and Jewel —

for the endless support, encouragement,

and inspiration you have

provided me throughout my life.

INTRODUCTION

Climate change is a crisis of global scale that poses a significant threat to many species, populations, and ecosystems (Thomas et al., 2011; Field et al., 2014). At its worst, climate change will drive some species to extinction (Stanton et al., 2014). Identifying which species are most vulnerable to climate change is vital for guiding effective conservation efforts (Dawson et al., 2011; Stanton et al., 2014). Many different factors contribute to species vulnerability, such as population size, reproduction rate, dispersal ability, and other life history traits, as well as extrinsic factors such as the potential for habitat loss and climate-change driven shifts in community structure (Lawler et al., 2009; Traill et al., 2010; Pearson et al., 2014). Unfortunately, many of these biological and ecological processes are either poorly documented or poorly understood for a large number of species, which can result in high levels of uncertainty in vulnerability assessments (Pearson et al., 2006).

There are presently more than 1.4 million known species of plants and animals that fall into this category of "known unknowns" — species with limited available data or species whose conservation status have simply not yet been assessed — along with countless millions more "unknown unknowns" (Mora et al., 2011; IUCN, 2014; Roskov et al., 2014). Stanton et al. (2014) assert that prevention of extinction due to climate change depends on timely identification of species vulnerability, as well as any change in conservation status. But how do we assess vulnerability when faced with this lack of species information? Moreover, how can we predict the consequences of climate change before its effects are observed at the species level? By the time such effects are directly observable at a population level, it may already be too late for meaningful and effective conservation actions (Hannah, 2011).

The climate change literature is rife with numerous types of forecasting tools that seek to measure impacts on species: extinction risk due to climate change has been quantified using life history and spatial habitat characteristics (Pearson et al., 2014; Stanton et al., 2014); vulnerability assessments combine trait-based species data with future projections of climate (Thomas et al., 2011; Young et al., 2012; Foden et al., 2013a); species distribution models correlate environmental conditions with species presence to predict how distributions will change with the climate (Hall, 2000; Manel et al., 2001; Guisan et al., 2002; Prasad et al., 2006; Cutler et al., 2007); deterministic models such as integrodifference equations are used to model the ability to keep pace with climate change through growth and dispersal (Zhou and Kot, 2011); dynamic range models incorporate Bayesian analysis to account for additional biotic parameters (Pagel and Schurr, 2012); and many other types of models (Lawler et al., 2006). Deciding which model to employ in what circumstances can be a difficult task: each come with their own assumptions, advantages and disadvantages, and can often yield different results (Lawler et al., 2006; Pagel and Schurr, 2012). Many of these models are computationally expensive, require specialized knowledge of species traits, and can be difficult to employ efficiently across a large number of species.

In this paper, I attempt to bridge this gap between simplicity and objectivity. I propose two new metrics for assessing aspects of species vulnerability that are completely objective and rely only on the barest minimum of species information. In the first chapter I develop these metrics and explore their robustness and reliability. In the second chapter, I apply them to 400 different species of trees, amphibians, mammals, and birds, and compare the results with three other methods of vulnerability assessment to determine how much they agree with current existing models, and how much new information they provide. Finally, I highlight some species that I believe are currently more vulnerable to climate change than is currently recognized, based on the results of this study.

Chapter 1

QUANTIFYING SENSITIVITY AND EXPOSURE

A common framework describes three fundamental aspects of climate change vulnerability: sensitivity, the degree to which the ability of a species to persist depends on its climate; exposure, the extent to which it will experience climate change across its range; and adaptive capacity, the ability to adapt to changes in climate, typically through evolutionary responses, dispersal, and phenotypic plasticity (see Figure 1.1) (Williams et al., 2008; Dawson et al., 2011; Foden et al., 2013a,b). These three dimensions broadly delineate four different categories of vulnerability in which species can be placed:

The **most vulnerable** species are ones that are highly sensitive to climate change, will likely be exposed to significant changes in climate in the future, and have little capacity to adapt to these changes. Species in this category face dramatic declines in population and habitat, and concerted conservation efforts are likely needed to prevent possible extirpation or extinction.

Species that are both sensitive and exposed but have a high adaptive capacity can be thought of as **potential adapters** to climate change. Although these species may experience adverse effects of climate change, they are expected to be able to cope through a variety of mechanisms such as dispersal or genetic adaptation. Nonetheless, adaptation can be a slow and gradual process, and they may still be at considerable risk. They will likely survive without human intervention, but these populations should be monitored for any change in status.

Species that have low adaptive capacity and are likely to be exposed but are not considered sensitive to climate change can be considered **potential persisters**. These species can tolerate a wide range of climatic conditions or not inherently dependent on ecological processes driven by climate, and are therefore relatively unaffected by changes. They are considered less at risk, but should be monitored for changes.

Finally, species that are sensitive and with low adaptive capacity but are not likely to be exposed to climate change have a **high latent risk**. They are not currently judged to be at risk from climate change, but future changes or unforeseen consequences of climate change could increase their vulnerability.

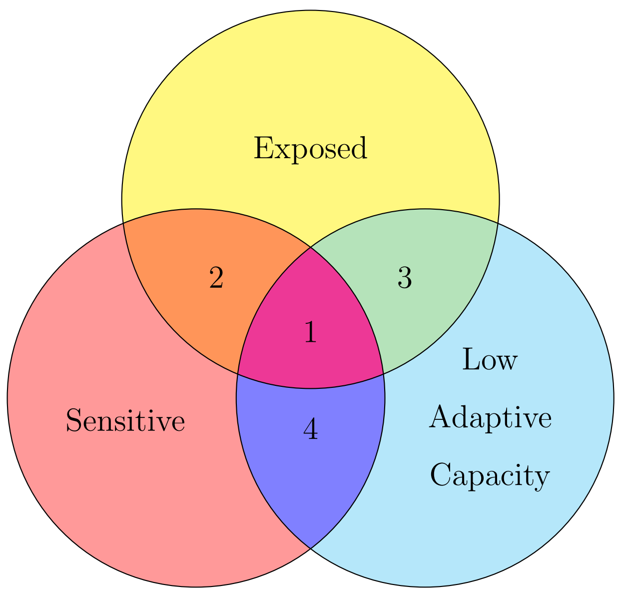

Figure 1.1: A common framework for species vulnerability to climate change. Species fall into four categories of vulnerability: (1) the most highly vulnerable species; (2) potential adapters; (3) potential persisters; and (4) species with a high latent risk. (Adapted from Foden et al., 2013a.)

These categorizations are particularly useful for designing management strategies that look beyond current and historical population trends, and can be proactive rather than reactionary. Using this framework, we propose two new metrics for objectively quantifying key aspects of species sensitivity and exposure to climate change.

It has been demonstrated that population distributions at the continental scale are largely driven by climate processes (Pearson and Dawson, 2003). This relationship is often used in species distribution modeling to describe a species' habitat preference and realized niche, as well as to predict future changes in distribution in response to climate change (Guisan et al., 2002; Lawler et al., 2006; Cutler et al., 2007; Pagel and Schurr, 2012). Our metric of sensitivity, which we call **climate breadth**, likewise takes advantage of this property. If a species is capable of thriving in a broad range of climates, we would expect it to be less sensitive to climate change than a species that can only tolerate a narrow range of climatic conditions. Climate breadth quantifies this sensitivity, and is a measure of the variability in climate across a species range. The higher the climate breadth, the less sensitive to climate change we expect a species to be. Climate breadth is itself a unitless measure, but one that provides us with a relative means of comparison between different species.

Similarly, we quantified exposure to climate change by measuring the differences in historical climate values and future scenarios across a species range; we call this the **index of exposure** (IE). A species with a high IE is expected to experience greater future change in climate.

We applied these metrics to 400 different species of amphibians, birds, mammals, and trees endemic to the Western United States. We then performed a sensitivity analysis of the two metrics to test their consistency across different climate datasets, different scales, and quality of distribution data.

1.1 Materials and Methods

1.1.1 Climate data

Climate datasets consisted of 40 annual, seasonal, and monthly bioclimate variables from the Climate WNA database (Wang et al., 2012), based on the PRISM dataset (Daly et al., 2002), and downscaled to a 1-km^2 resolution (see Appendix I for the list of variables). The historical dataset was based on averaged climate records from

1961–1990. Future datasets consisted of climate projections from three different global climate models (BCCR BCM2.0, CCCMA CGCM3, CSIRO MK 3.0) run for the SRES A2 greenhouse-gas emissions scenario from the IPCC's Fourth Assessment Report (Solomon, 2007). The study area covered much of the western half of North America, from 25–60°N and 140–100°W (see Figure 1.2).

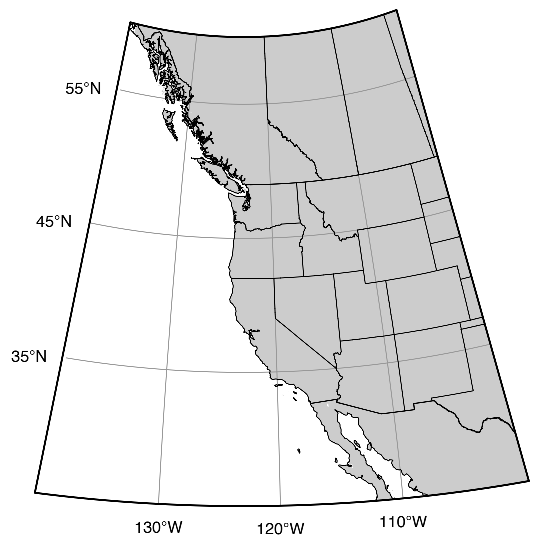

Figure 1.2: Extent of climate dataset

Principal component analysis (PCA) was used to minimize the correlation between the variables, and to center and scale them appropriately (Jolliffe, 2005). The number of significant components was determined using Frontier's broken-stick method (Frontier, 1976; Jackson, 1993), which produced two PCA-transformed variables that collectively accounted for 85.9% of the variation of our original climate data. To maintain consistency across datasets, the loadings of the historical PCA were used to transform the future data.

1.1.2 *Species data*

Digital distribution maps were obtained from the USGS's digital representations of Little's "Atlas of United States Trees" (U.S. Geological Survey, 2014) for trees, and from the IUCN's Red List of Threatened Species database for animals (IUCN, 2014). The study was restricted to species that had at least 95% of their distribution within the study area. Range maps were rasterized to the same resolution as the climate data, and interpreted as presence/absence maps: any grid cell with a center lying inside a species distribution was labeled as a presence, and any grid cell with a center falling outside was labeled as an absence. For birds, only year-round and breeding ranges were used.

All data processing and analysis was done in R with the `maptools` and `raster` packages (Bivand and Lewin-Koh, 2014; Hijmans, 2014).

1.1.3 *Quantifying sensitivity*

We quantified sensitivity to climate change with climate breadth. We first calculated the median value of each of the PCA-transformed historical climate variables across the entire study area; we then calculated the Euclidean distance between the historical climate values and the historical climate medians. This process yielded a value at geographic location that reflected the difference between that point and the median climatic conditions across the study area. We denote the median of these distances by $\tilde{\mu}_H$, and refer to this as the background climate variation.

Next, for each species, we calculated the median $\tilde{\mu}_i$ of each of the i PCA-transformed climate variables across the species' geographic range. We then calculated the Euclidean distance between the historical climate values and the historical climate medians for every data point within the species distribution; this process yielded a set of distances that reflected the differences from the median climatic conditions across the species range (see Figure 1.3). Finally, these distances were scaled by the background climate variation $\tilde{\mu}_H$. We define climate breadth as the median of these distances. This is written formally as

$$\sigma_c = \underset{j}{\mathrm{Median}} \left(\frac{100\sqrt{\sum_{i \in C}(x_{ij} - \tilde{\mu}_i)^2}}{\tilde{\mu}_H} \right), \tag{1.1}$$

where σ_c is the climate breadth, C is the set of significant PCA components, j is in the set P of raster cells indicating presence of the species, x_{ij} is the value of historical PCA variable i at j, $\tilde{\mu}_i$ is the median value of variable i over P, and $\tilde{\mu}_H$ is the median Euclidean distance between the climate medians of the entire climate dataset.

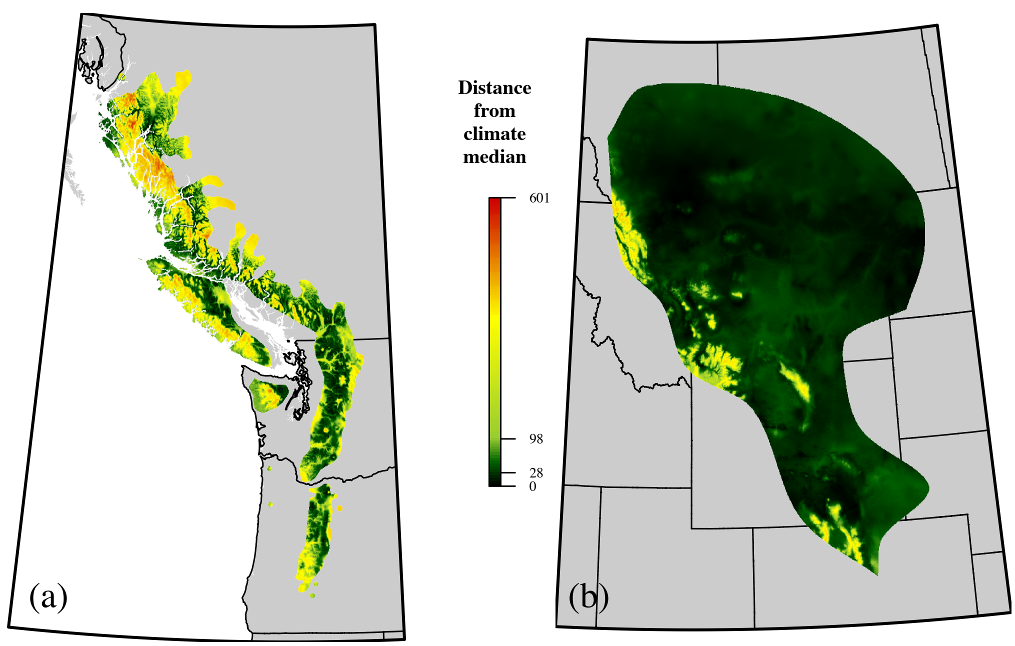

Figure 1.3: Sensitivity maps for (a) Pacific silver fir (*Abies amabalis*), with a relatively high climate breadth ($\sigma_c = 98.39$), and (b) McCown's longspur (*Calcarius mccownii*), with a relatively low climate breadth ($\sigma_c = 28.08$).

To illustrate, we provide a simple toy example species, and calculate its climate breadth in three steps. Consider a study area of 9 km^2, a species occupying one-third of this area, and two climate variables describing the region:

Species presence

0	1	0
1	1	0
0	0	0

Climate variable 1

4.5	4.5	5
5	6	5.5
6	6.5	7

Climate variable 2

3	3.1	3.1
2.8	2.9	3.3
3	3.2	3.1

Step 1: finding the median climate values across a species' range

Considering only the locations where the species is present, we see that the median values of the climate variables are $(\tilde{\mu}_1, \tilde{\mu}_2) = (5, 2.9)$.

Step 2: calculating the distances from the climate medians

For each location j of species presence, we calculate the Euclidean distance d_j between the climate values at that point and the medians:

$$d_1 = \sqrt{(4.5-5)^2 + (3.1-2.9)^2} = 0.5385$$
$$d_2 = \sqrt{(5-5)^2 + (2.8-2.9)^2} = 0.1$$
$$d_3 = \sqrt{(6-5)^2 + (2.9-2.9)^2} = 1$$

The median of these distances is 0.5385.

Distances from medians

	.54	
.1	1	

Step 3: normalizing the median to the study area

We calculate the Euclidean distances across the entire study area similarly:

Distances from medians

1	1	.5
.58	.54	.2
.5	1	1.5

The median of these distances is $\tilde{\mu}_H = 0.5831$. Our species therefore has a climate breadth of

$$\sigma_c = 100 \cdot \frac{0.5385}{0.5831} = 92.4.$$

Climate breadth is similar to the median absolute deviation (a robust measure of central tendency), but extended to accommodate higher-dimensional data and normalized for the study area (Donoho and Huber, 1983). Normalization provides a convenient interpretation of climate breadth; a species with a climate breadth of 100 has the same median amount of climate variability across its range as the background climate variation.

1.1.4 Quantifying exposure

To measure climate exposure, we calculated the Euclidean distance between the future and historical climate values for every data point within the species range. This yielded a set of distances that collectively described the difference between future and historical climatic conditions across a geographic distribution. We then normalized these distances to the study area and found the median of these distances (see Figure 1.4). We define this quantity as the index of exposure (IE), calculated by

$$\mathrm{IE} = \underset{j}{\mathrm{Median}} \left(\frac{100\sqrt{\sum_{i \in C}(x_{ij} - f_{ij})^2}}{\tilde{\mu}_F} \right), \tag{1.2}$$

where x_{ij} is the value of historical climate variable i at j, f_{ij} is the value of future climate variable i at j, and $\tilde{\mu}_F$ is the median Euclidean distance between the historical and future climate values across the entire climate dataset. A large IE indicates that climatic conditions will remain largely the same across a species range; conversely, a small IE indicates greater changes in climate. Normalization scales IE similarly: a species with an IE of 100 will experience the same median amount of climate change as the entire study area.

Different climate models that project future climate values will give different IEs for the same species. For this study, we considered three different climate models under the same emissions scenario, and used the average index of exposure (AIE) between the three models.

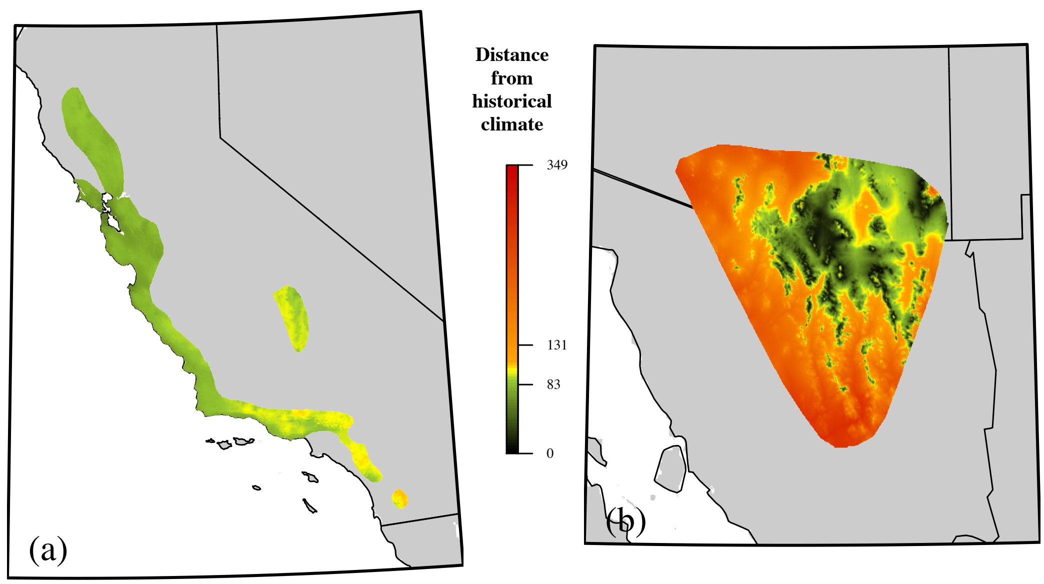

Figure 1.4: Exposure maps under the CSIRO climate scenario for (a) the California newt (*Taricha torosa*), illustrating a relatively low index of exposure (IE = 83.4), and (b) the Sierra Madre ground squirrel (*Spermophilus madrensis*), with a relatively high index of exposure (IE = 131.2).

1.1.5 Effects of scale, data, and data quality

As defined, the values of climate breadth and IE are not solely intrinsic properties of a species; their values are in part functions of which future climate scenario is considered, the resolution of the climate data, and the types of climate variables used. We quantified these effects in three ways. In the first, the climate breadths and IEs of all 400 species were calculated using three different sets of future climate projections. In the second, climate breadths and IEs were calculated using 19 different spatial resolutions of historical and future climate data, from 1-km^2 to 10,000-km^2. To ensure a meaningful sample size, any species that had a distribution area less than 100 times the area of the resolution of the climate data after rasterization were discarded. In the third, climate breadths and IEs were calculated using 10 different subsets of the forty bioclimate variables, ranging from two variables (mean annual temperature and mean annual precipitation) up to the full forty. Each subset of climate data was constructed to be a plausible dataset, representative of those used in climate change studies, and each underwent its own PCA transformation. (See Appendix III for the subsets of variables used.)

Likewise, the quality of the species distribution data will affect the values of climate breadth and IE. Interpreting continental-scale range maps as presence/absence data will typically yield spurious presences, due to the differences in resolution between the range map and the climate data. Range maps are often used to delineate general habitat preference, and will misclassify unsuitable habitat due to its proximity to suitable habitat (Hurlbert and White, 2005; Hurlbert and Jetz, 2007). An example of this can be seen in the range map of the noble fir, *Abies procera*, which is shown to cover Mount Rainier, despite it being heavily glaciated and devoid of trees above an elevation of 2200m (Google Maps, 2014). To quantify the effects of miscategorized distribution data, presence data with unreasonably high leverage were naively removed from range maps. For each species, the set of distances from the climate medians was calculate. Any distance outliers (any point not within 1.5×IQR of the lower or upper quartiles) were removed, since these data represented the locations that could be considered too climatically extreme for species survival; climate breadths and IEs of all 400 species were then recalculated with the outliers removed (see Figure 1.5).

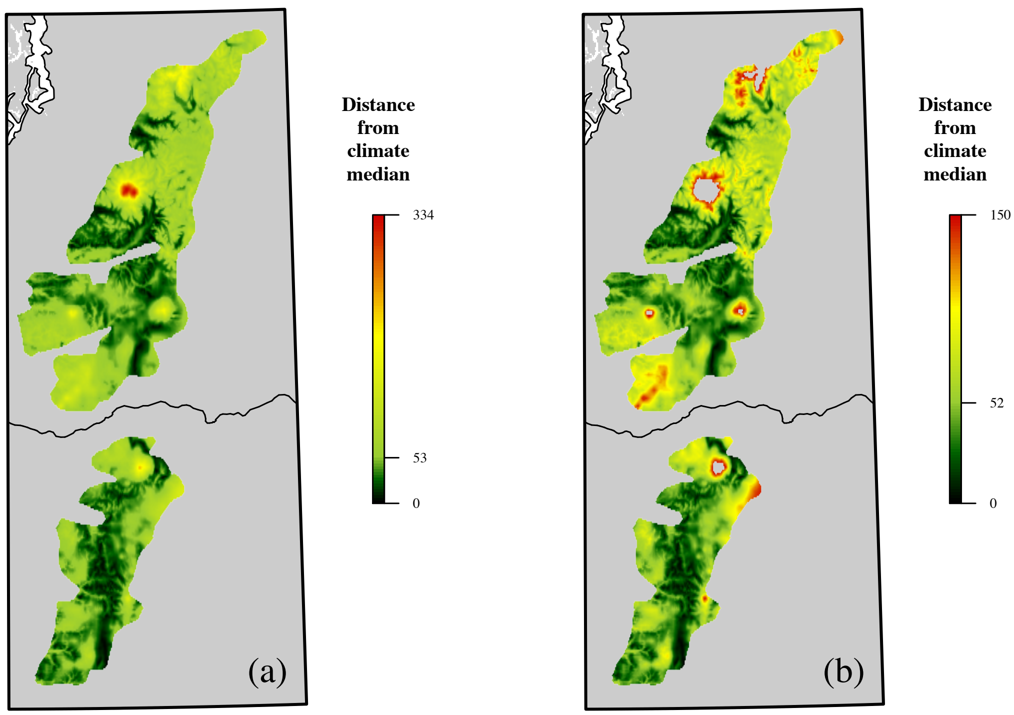

Figure 1.5: Sensitivity map for *Abies procera* with (a) the full range included, and (b) the climatic outliers removed. The locations removed correspond to the peaks of Mount Rainier, Mount St. Helens, Mount Adams, Mount Hood, and the North Cascades.

1.2 Results

1.2.1 Climate breadth

A large range of climate breadths was found across the 400 species. Climate breadths ranged from a minimum of 6.15 to a maximum of 113.9, and were normally distributed (mean = 47.59, sd = 21.47, Shapiro-Wilk $W = 0.978$, $p < 0.0001$). Significant differences were observed between the median climate breadths of different taxa; trees had the lowest median climate breadth, followed by amphibians, mammals, and birds had the highest (see Figure 1.6). These differences are likely a consequence of species mobility; trees must be able to tolerate their climates year-round, resulting in likely narrower climate niches. Conversely, birds are highly mobile, and often move by tracking changes in climate by season, resulting in larger climatic niches as defined.

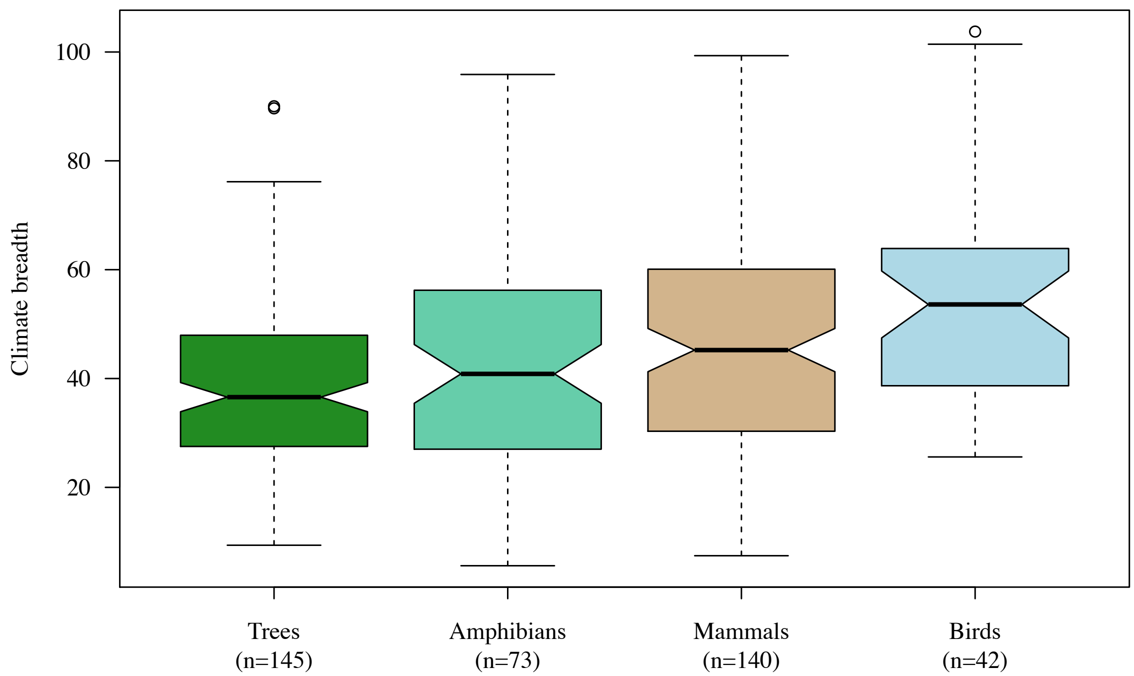

Figure 1.6: Boxplots of climate breadths by taxon. Nonoverlapping notches in the boxplots indicate a significant difference of the medians (McGill et al., 1978).

A moderate correlation was observed between climate breadth and the log of distribution area in km^2 ($r = 0.52$, $p < 0.001$) (see Figure 1.7). This follows our intuition that a species that is geographically restricted to a small area would experience less variation in climate across its distribution. Nonetheless, it is possible for a species to be widespread but have a low measure of climate breadth, as long as there is a large geographic area with similar climate, as in the case of the greater sage-grouse (*Centrocercus urophasianus*, $\sigma_c = 36.6$, habitat area ≈ 2.25 million km^2). Conversely, a species can be geographically limited but have a high measure of climate breadth if its range is climatically diverse, as in the case of the Panamint kangaroo rat (*Dipodomys panamintinus*, $\sigma_c = 90.4$, habitat area ≈ 3800 km^2).

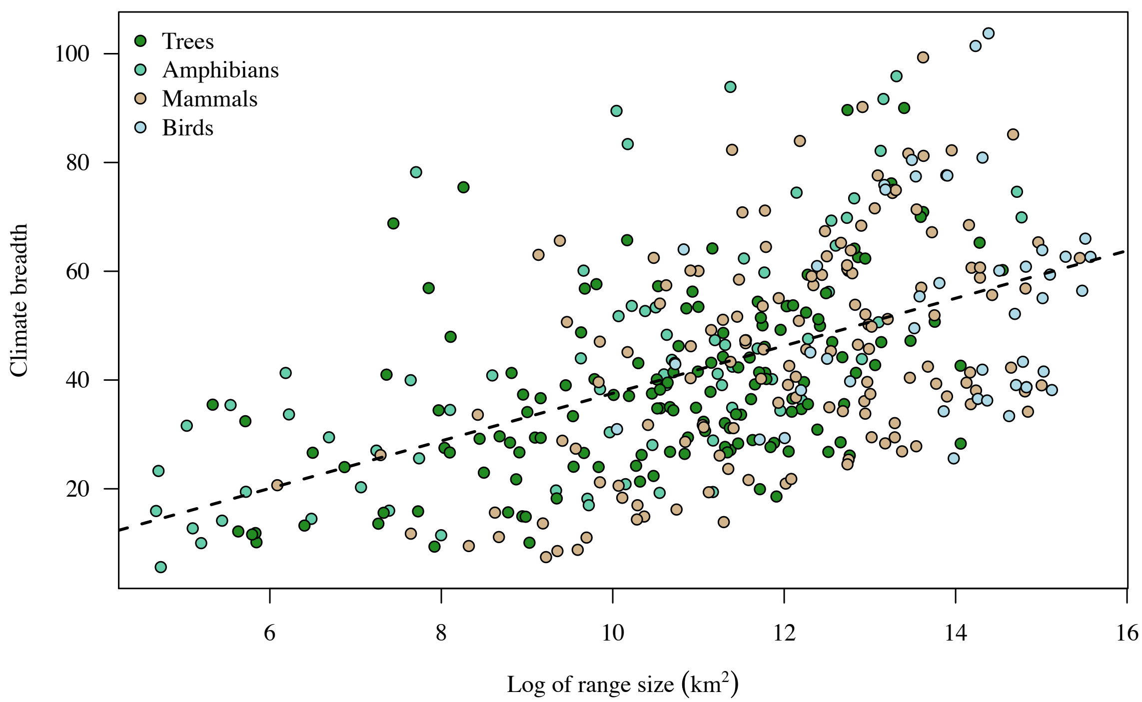

Figure 1.7: Scatterplot indicating the correlation ($r = 0.52$) between species range size and climate breadth.

1.2.2 *Index of exposure*

A large range of indices of exposure was also observed. Averaging the IEs of the three future climate scenarios for each species, the average index of exposure (AIE) ranged from a minimum of 79.13 to a maximum of 128.8, and also appeared to be normally distributed (mean = 102.3, sd = 9.07, Shapiro-Wilk $W = 0.987$, $p < 0.002$). Differences in IE values between taxa were less pronounced than with climate breadth (see Figure 1.8); this is likely because the changes in climate a species might experience is more a consequence of where it is geographically distributed.

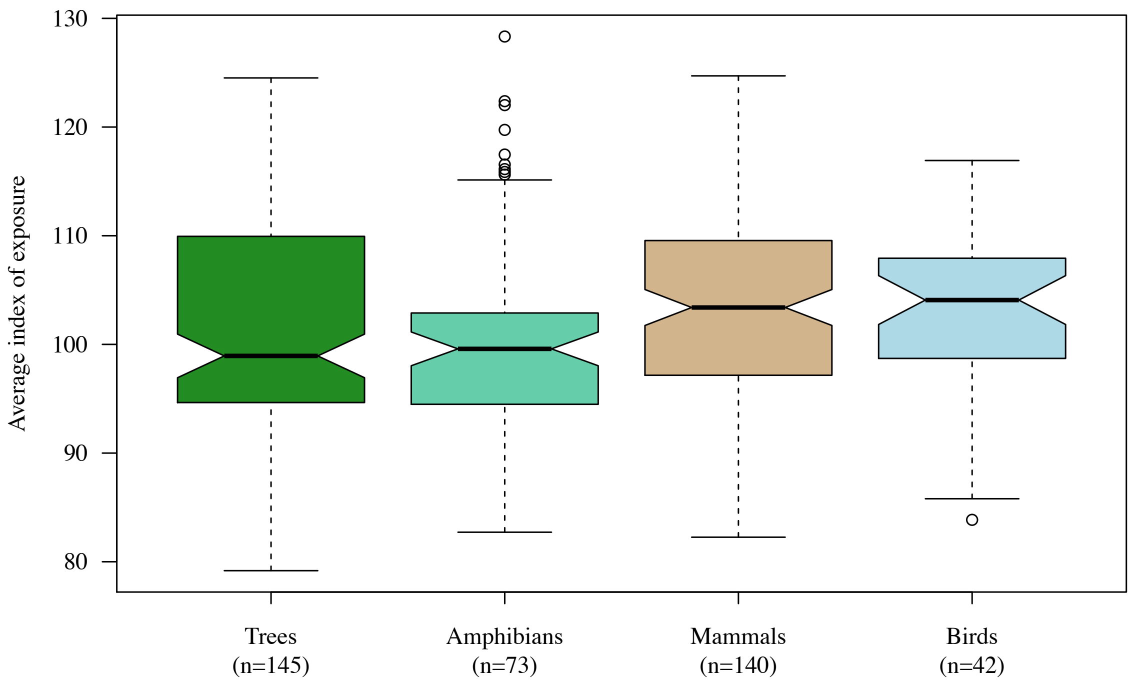

Figure 1.8: Boxplots of the indices of exposure by taxon, averaged across the three future climate scenarios.

There was no correlation between AIE and the log of distribution size ($r = 0.103$, $p = 0.04$) (see Figure 1.9). This suggests that the amount of climate change a species will experience is more a function of the type of habitat (e.g., coastal, desert) and geographical location (e.g., latitude) that it favors, rather than the extent of its distribution.

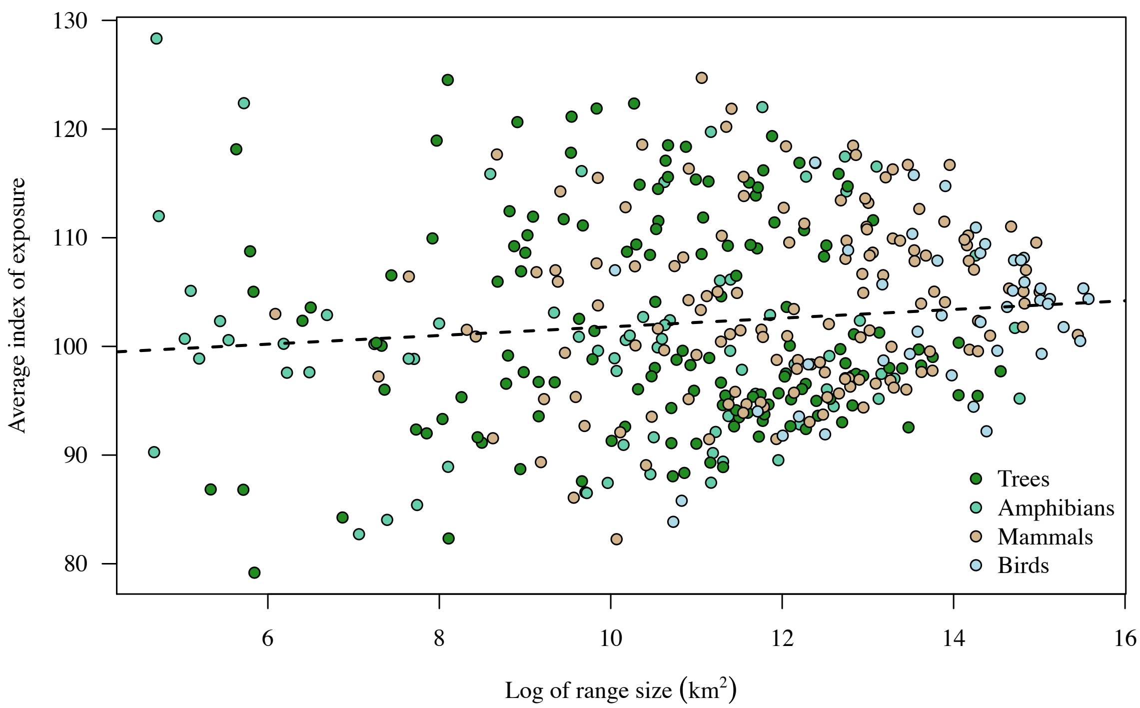

Figure 1.9: Scatterplot indicating the lack of correlation ($r = -0.032$) between species range size and AIE.

Comparing the two metrics, no correlation was observed between climate breadth and AIE ($r = -0.083$, $p = 0.1$) (see Figure 1.10). This result demonstrates the independence of sensitivity and exposure: while species can be sensitive to the affects of climate change they may not be exposed to it, such as the coast live oak (*Quercus agrifolia*, $\sigma_c = 30.4$, AIE $= 88.8$, habitat area $\approx$ 81,000 km^2). Conversely, species may be faced with a great deal of exposure to climate change, but will be more resilient due to less sensitivity, as in the case of Gambel's quail (*Callipepla gambelii*, $\sigma_c = 84.99$, AIE $= 115.7$, habitat area $\approx$ 750,000 km^2).

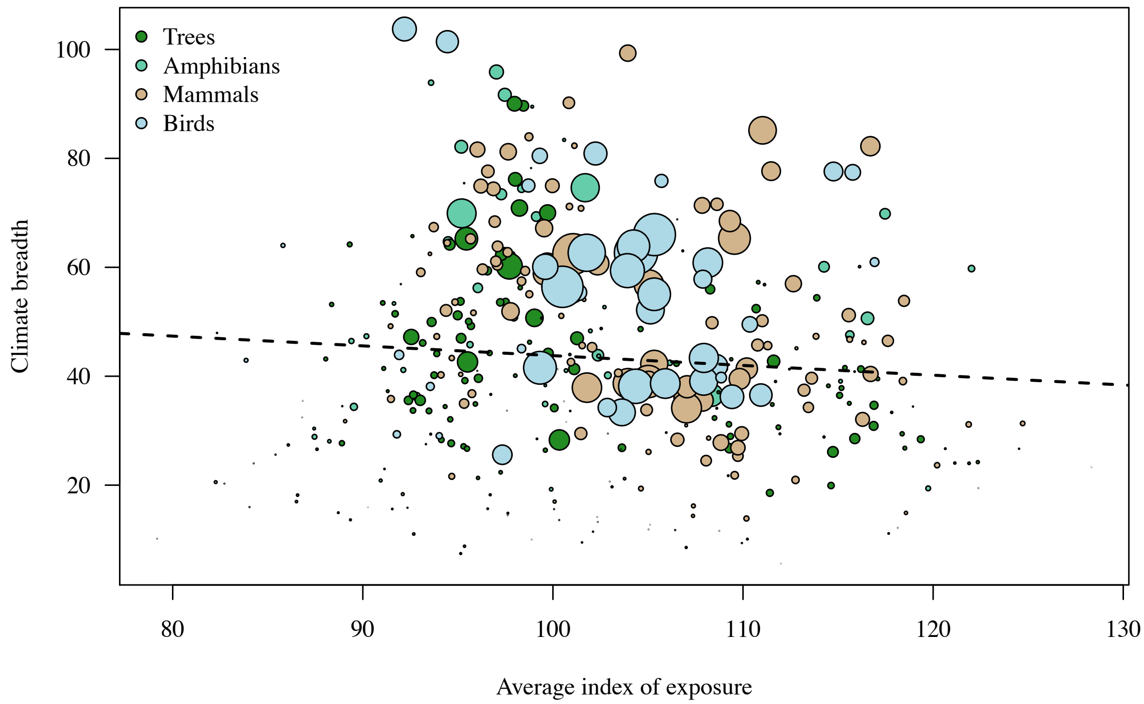

Figure 1.10: Scatterplot indicating the lack of correlation ($r = -0.083$) between AIE and climate breadth. Point size corresponds to the range size of each species.

With joint normality between climate breadth and AIE sufficiently established, as well as a large enough sample size from which to compare species, we can now combine the two metrics to determine relative vulnerability. Each species is categorized by which quantile of sensitivity and exposure it falls in, where the first quantile of sensitivity is associated with the last quantile of climate breadth and the first quantile of exposure is associated with the first quantile of AIE; a species in the highest quantiles of sensitivity and exposure would be considered most vulnerable, and a species in the lowest quantiles least vulnerable. This can be done in a number of different ways. Species can be placed in the categories introduced at the beginning of the chapter by dividing the distributions at their medians; any species with a climate breadth lesser than the median climate breadth and AIE greater than the median AIE, for example, could be considered as a potential adapter or highly vulnerable, depending on its adaptive capacity (see Table 1.1a). Alternatively, a simple sum of the quantile ranks of sensitivity and exposure would give a finer gradation of categories, and relax the need for information on adaptive capacity for proper categorization. Dividing the distributions into quartiles, this method yields seven distinct categories of vulnerability (see Table 1.1b).

		Sensitivity			
	(a)	1st	2nd	3rd	4th
Exposure	1st	17	27	26	30
	2nd	44	25	14	17
	3rd	24	24	31	21
	4th	15	24	29	32

		Sensitivity			
	(b)	1st	2nd	3rd	4th
Exposure	1st	17	27	26	30
	2nd	44	25	14	17
	3rd	24	24	31	21
	4th	15	24	29	32

Table 1.1: Number of vulnerable species by quartile rank of climate breadth and AIE, corresponding to sensitivity and exposure, respectively. Depending on adaptive capacity, table (a) has categorized species as not threatened or low adaptive capacity (blue), sensitive or at high latent risk (pink), exposed or potential persisters (yellow), and most vulnerable or potential adapters (magenta). Table (b) categorizes species according to the sum of their quartile ranks. Redder colors correspond to more vulnerable species; greener colors correspond to less vulnerable species.

1.2.3 Effects of scale, data, and data quality

Considerable differences were found in the IEs of individual species, depending on the future scenario used to calculate them. The IEs calculated with the CGCM3 and BCCR scenarios agreed most closely, differing by an average of 10.1 ± 8.7. By contrast, the average difference between CGCM3 and CSIRO IEs was 16.1 ± 6.4, and 15.6 ± 8.1 between the CSIRO and BCCR scenarios. This result highlights the uncertainties involved in predicting future impacts of climate change. The Sonoran pocket mouse (*Reithrodontomys burti*, $\sigma_c = 11.51$, range area $\approx$ 67,000 km^2), for example, is predicted to experience a low, moderate, or high amount of climate change (BCCR = 81.4, CSIRO = 108.7, CGCM3 = 124.9). In contrast, the Allen's hummingbird, (*Selasphorus sasin*, $\sigma_c = 25.52$, range area $\approx$ 45,000 km^2) is consistently predicted to experience low exposure (BCCR = 81.9, CSIRO = 79.7, CGCM3= 89.7).

Both metrics demonstrated consistency across a broad range of scales (see Figure 1.11). A one hundred-fold decrease in data resolution changed climate breadths by an average of $3.9 \pm 3.3\%$, and the climate breadths relative to other species changed imperceptably (Spearman's $\rho = 0.994$). In general, the mean percent change Δ_{σ_c} in climate breadth can be approximated by

$$\Delta_{\sigma_c} = 1.37 \log x, \tag{1.3}$$

where x is the spatial resolution of the data in square kilometers. Similarly, the mean percent change Δ_{IE} in IE is given by

$$\Delta_{IE} = 0.048 \log x, \tag{1.4}$$

which amounts to an average of $0.19 \pm 0.18\%$ with a one-hundred fold decrease in resolution, with virtually no change in relative ranking (Spearman's $\rho = 0.999$).

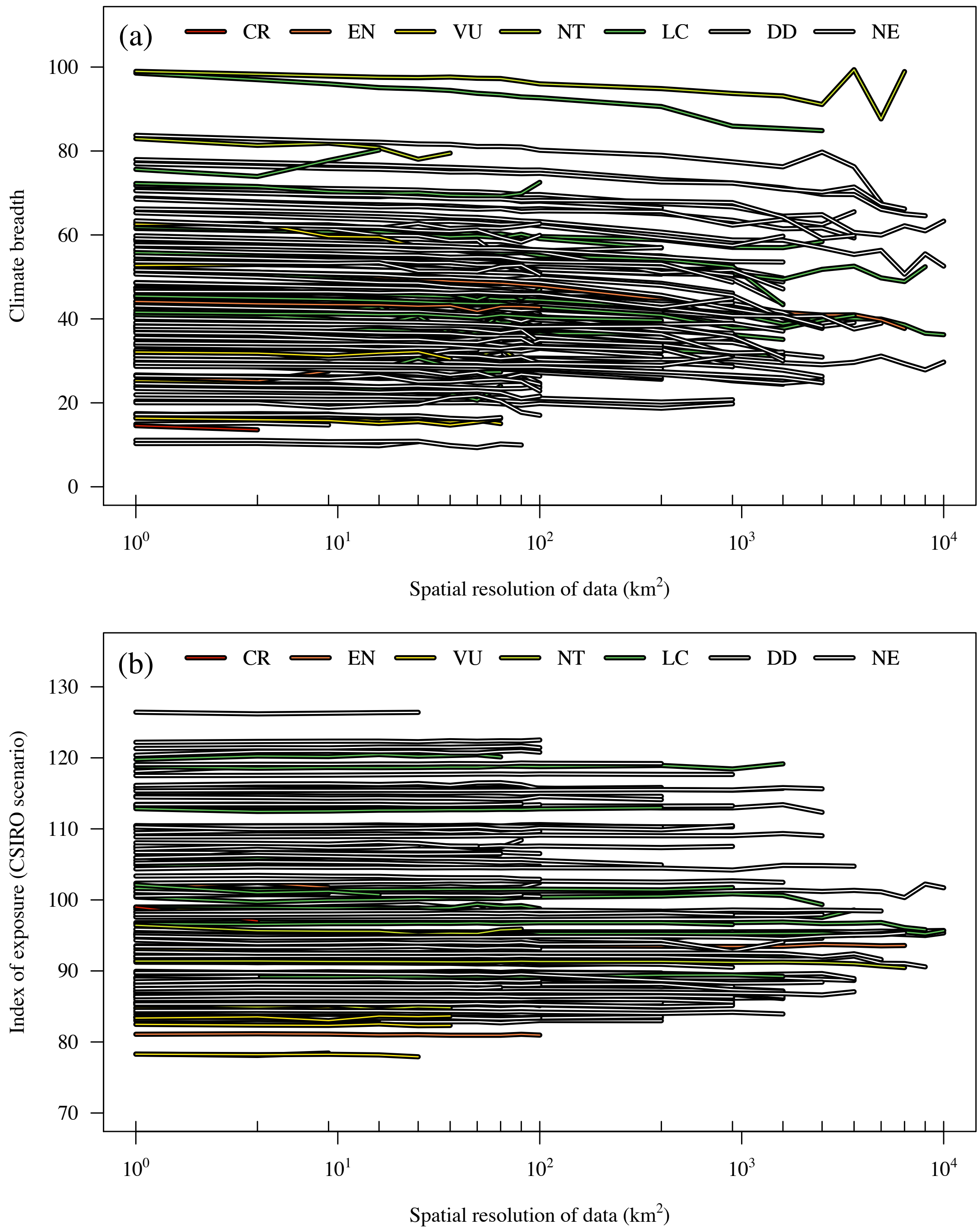

Figure 1.11: Variation in (a) climate breadth and (b) IE of 145 species of trees calculated across 19 different resolutions of climate data. The tick marks above the (log scale) axes of spatial resolution represent the resolutions that were sampled. Line colors correspond to IUCN Red List status.

Climate breadth varied considerably depending on which bioclimate variables were used to calculate it (see Figure 1.12a). In particular, there were large differences in values between datasets that contained seasonal variables (n = 16, 23, 32, 36, 40) and datasets that did not (n = 2, 8, 20). Despite this, there was little change in the relative ranking of species (mean Spearman's $\rho = 0.939$) (see Table 1.2), especially as more variables were incorporated into the model.

	Number of bioclimate variables							
	2	8	16	20	23	32	36	40
2		0.89	0.95	0.76	0.92	0.88	0.88	0.92
8			0.95	0.89	0.94	0.95	0.96	0.96
16				0.87	0.98	0.97	0.97	0.98
20					0.92	0.94	0.96	0.93
23						0.99	0.98	0.99
32							0.99	0.99
36								0.99

Table 1.2: Spearman's ρ of the climate breadths of 145 tree species between each constructed climate dataset.

The differences between datasets that contained seasonable variables and datasets that didn't were even more pronounced for IE (see Figure 1.12b). The relative rankings of IE from the dataset with two variables bore little resemblance to other models, but the rankings maintained increasingly more consistency across datasets with increasingly more variables (see Table 1.3). The climate datasets that were in greatest disagreement with others were ones that did not contain any seasonal variables ($n = 2, 8, 20$), which help describe aspects of inter-annual climate variability. Since IE is a measure of the amount of climate change that occurs in a species' range, it makes sense that using more climate variables would yield a more accurate and meaningful estimate of exposure.

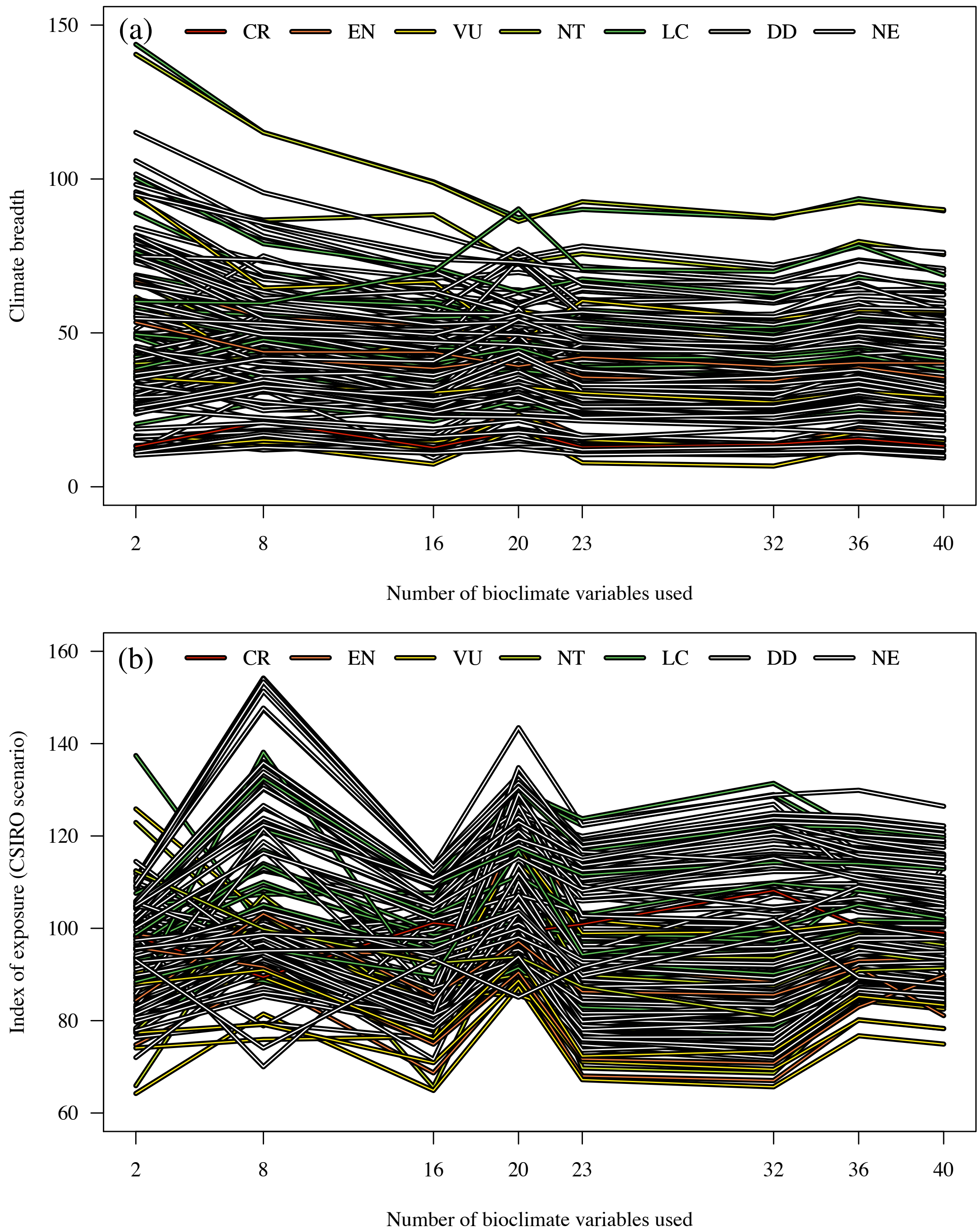

Figure 1.12: Variation in (a) climate breadth and (b) IE of 145 species of trees calculated with eight different combinations of bioclimate variables. $n = 2, 8, 20$ represent datasets that contain only annual variables.

	Number of bioclimate variables							
	2	8	16	20	23	32	36	40
2		0.52	0.70	0.10	0.38	0.33	0.36	0.40
8			0.74	0.53	0.63	0.58	0.67	0.68
16				0.55	0.83	0.83	0.82	0.85
20					0.86	0.86	0.91	0.88
23						0.98	0.97	0.97
32							0.97	0.97
36								1.00

Table 1.3: Spearman's ρ of the indices of exposure (CSIRO scenario) of 145 tree species between each constructed climate dataset.

Spurious presence data proved to have little effect on climate breadth or AIE; values were similar, regardless of whether the full distribution map was used or whether distance outliers were removed. Removing the outliers decreased the climate breadth by an average of $3.1 \pm 2.7\%$, and the relative ranking was negligibly affected (Spearman's $\rho = 0.998$). Outlier removal decreased AIE by only $0.16 \pm 0.46\%$, and the relative ranking of species was virtually identical ($\rho = 0.999$).

1.3 Discussion

One of the greatest strengths of climate breadth and the index of exposure is that they can identify species that are sensitive or exposed to climate change with little information about the species itself. Using nothing more that range maps that specify general habitat preference, our methods offer objective, spatially explicit results that give insight into the role that climate plays in shaping species' ranges. In the context of the 1.4 million known species whose conservation statuses are still unassessed, our methods provide us a clear strategy for separating the proverbial wheat from the chaff, to identify the subset of species most potentially vulnerable to climate change. And, perhaps more importantly, we can do this before we start seeing the inevitable consequences of vulnerability, such as decreasing population numbers or shrinking habitat.

Stanton et al. (2014) quantified the probability of extinction of species due to climate change as a function of the warning times that we have once they are identified as vulnerable, and concluded that we must identify vulnerable species as early as possible in order to maximize our chances for conservation. Pearson et al. (2014) demonstrated how different spatial and life history traits can predict the risk of extinction of a species due to climate change. In particular, the amount of occupied area, spatial correlation of environmental variability, and breadth of climatic niche in temperature and precipitation were significant predictors for risk of extinction. By definition, climate breadth quantifies the breadth of climatic niche of a species; we also saw that it is correlated with the amount of occupied area. Furthermore, the spatial correlation of environmental variability could be measured by quantifying the spatial autocorrelation of the distances from the climate medians obtained when calculating climate breadth. Since many significant spatial traits are encapsulated by climate breadth, it is reasonable to infer that it could be used to quantify the spatial aspects that contribute to the extinction risk of a species due to climate change.

The consistency across a wide variety of spatial scales is in part a consequence of the high degree of spatial autocorrelation in the climate data (Dormann et al., 2007). Locations that are geographically close to one another will tend to have similar climate values, which amounts to very little loss in information when using a coarser resolution of climate data. This also implies that there is little to be gained from using finer scale climate data alone.

The consistency across different datasets is largely due to the choice in normalizing constants $\tilde{\mu}_H$ and $\tilde{\mu}_F$. Regardless of the climate variables used to measure climate breadth, these constants establish a reference point for the value of σ_c and IE, so that, e.g., the σ_c of any given species will be proportional to $\tilde{\mu}_H$.

It is important to note, however, that climate breadth suffers from some of the shortcomings of other species distribution models (Lawler et al., 2006; Pagel and Schurr, 2012). Climate breadth only measures the climatic variability of the realized niche of a species. Non-climatic constraints such as biotic interactions, dispersal ability, and landscape topography can prevent a species from populating habitat that is climatically suitable. Future novel climates might also favor a species, despite differing from the climate the species currently experiences. Indeed, this appears to be the case for the Lawson cypress (*Chamaecyparis lawsoniana*, $\sigma_c = 40.89$, AIE = 91.2); the conditions that *C. lawsoniana* currently favors are found at the climatic extremes of the study area, and future projections suggest a shift to climate conditions not currently found. Whether or not this will benefit the species remains to be seen.

IE only quantifies the magnitude of potential exposure to climate change, and not the direction. Under a given future climate scenario, it is possible for habitat to change favorably for a species, but that would not be measurably different from a shift toward unfavorable habitat. Western juniper (*Juniperus occidentalis*, $\sigma_c = 29.49$, AIE = 103.2, range area $\approx$ 171,000 km^2) has a relatively low climate breadth and large predicted changes in climate across its current range, but has experienced a sizable range expansion in the last century (Miller and Rose, 1999). This is largely attributed to human influences such as fire suppression and cattle grazing, but it is worth noting that *J. occidentalis* favors semi-arid to arid climates, and it is probable that future changes in climate it will continue to be favorable for this species. To properly assess the impacts of this change, one should also explore other methods such as species distribution models or dynamic range models.

Although our methods provide a useful technique to visualize the climatic variability in any given region of a species' range, the concept of climate breadth is only meaningful when applied to a species as a whole. Quaking aspen (*Populus tremu-*

loides) can be found throughout much of our study area, but its range extends well outside it. Conclusions based on its climate breadth within our study area would likely overestimate its sensitivity to climate change.

By no means do our methods provide a comprehensive assessment of any species. Intrinsic characteristics such as dispersal ability and extrinsic factors unrelated to climate such as biotic interactions will also contribute to species vulnerability; in the context of our framework, adaptive capacity must also be considered. Despite these limitations, climate breadth and IE provide a simple, objective quantification of species sensitivity and potential exposure to climate change. They are useful in studies of high scope in which a large number of species are compared, or in single-species studies to gain a better understanding of climate variability across a species' range. They could easily be adapted to abundance data by assigning weights to each distance in proportion to the population at each geographic location. They give results that are contrastable and consistent across a wide range of spatial scales and across a variety of climate datasets. When used in tandem with other assessment methods, these metrics can help to provide a more complete picture of species vulnerability. We recommend using climate breadth and IE as the first step of any vulnerability assessment.

Chapter 2

VULNERABILITY COMPARISONS

A wide variety of methods for assessing vulnerability are already in use to help guide environmental policy and resource management decisions throughout the world. They range from broad, continental-level analyses to micro-scale studies focused on regional subpopulations, and can incorporate many different types and sources of information.

In this chapter, we compare the results of three different methods of vulnerability assessment with our own: the International Union for Conservation of Nature's Red List of Threatened Species provides a rigorous and comprehensive database detailing the conservation status of thousands of species across the planet (IUCN, 2014). Despite its extensive efforts, the IUCN has been criticized for not sufficiently taking into account the effects of climate change, and some of these critics have responded by devising their own assessment methods (Thomas et al., 2011; Young et al., 2012; Foden et al., 2013a). Foden *et al.*'s method, in particular, utilizes the framework outlined at the beginning of Chapter 1. Finally, the Pacific Northwest Climate Change Vulnerability Assessment — a collaborative effort between different regional and governmental agencies — offers a more regionally-specific perspective (CCSD, 2014).

Between the contrasts of these three methods and our own, we hope to answer three questions: how well can climate breadth and AIE correctly identify species we understand to be vulnerable to climate change? How effective are climate breadth and AIE at identifying species we *don't* currently recognize as vulnerable? How strongly do our results agree with the results of others?

2.1 *The IUCN Red List*

The IUCN Red List is generally recognized as the most comprehensive account of species conservation status (Rodrigues et al., 2006). The Red List categorizes species into one of nine vulnerability categories, each rigorously defined by five criteria (A-E) that quantify variables such as population size, range area, habitat fragmentation, and population trends (IUCN, 2001) (see Figure 2.1). Several recent studies, however, have suggested that the Red List criteria do not adequately account for the impacts of climate change (Thuiller et al., 2005; Akçakaya et al., 2006; Hannah, 2011). This is especially concerning, given that climate threats to species might not be perceptible until it is too late to help them, due to the gradual effects of climate change. Others have concluded that Red List status does a satisfactory job of predicting extinction risk, provided that proper conservation actions are taken as soon as a species is categorized as Vulnerable or higher (VU+) (Stanton et al., 2014).

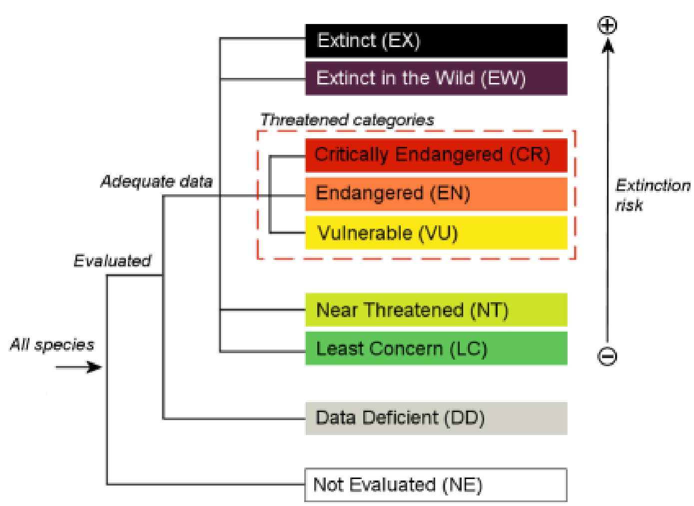

Figure 2.1: Framework for the IUCN's species categorization by conservation status (IUCN, 2014).

Climate breadth was compared to IUCN Red List status with Mann-Whitney U tests comparing the climate breadths of species in each threatened category with the climate breadths of species in higher threatened categories, e.g., Least Concern (LC) vs. Near Threatened or higher (NT+). IE was compared to IUCN Red List status similarly.

A strong general linear trend was found between the median climate breadths of the different evaluated conservation categories (weighted least squares, $n = 288$, $r^2 = 0.97$, $p < 0.001$). This is likely in part due to the use of range size as a criterion for IUCN conservation status, because climate breadth is correlated with range size. A significant difference was observed between the median climate breadth of species currently listed as Least Concern (LC) and the median climate breadth of species described as more threatened (NT+), i.e., Near Threatened (NT), Vulnerable (VU), Endangered (EN), or Critically Endangered (CR) (Mann-Whitney $U = 11637$, $n_1 = 209$, $n_2 = 79$, $p < 0.0001$). A similar difference was observed between NT species and those considered more threatened (VU+) (Mann-Whitney $U = 972$, $n_1 = 28$, $n_2 = 51$, $p < 0.01$). (See Figure 2.2a.)

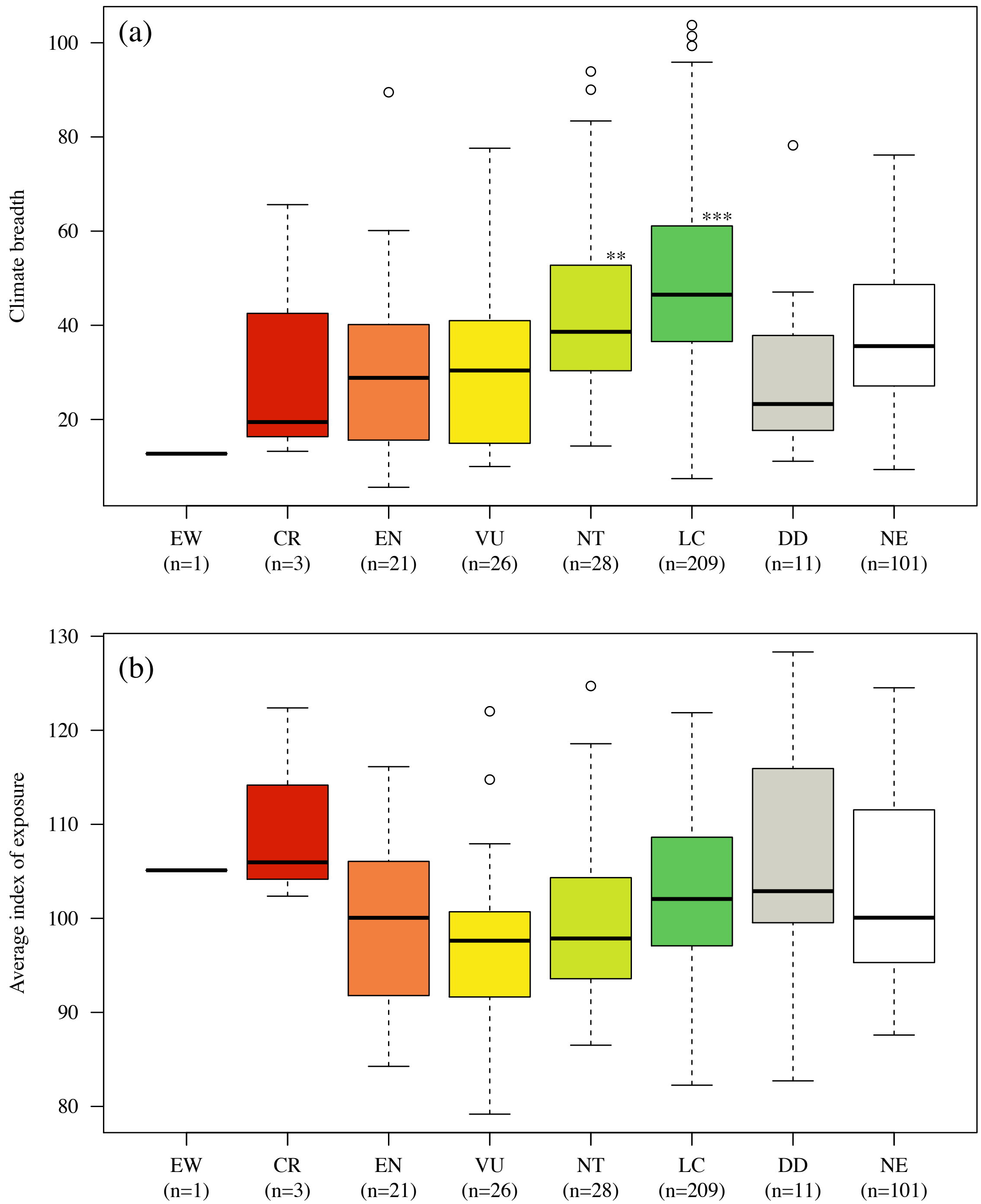

Figure 2.2: Boxplots of (a) climate breadths and (b) average indices of exposure (AIE) by current IUCN conservation status. IUCN categories are Extinct in the Wild (EW), Critically Endangered (CR), Endangered (EN), Vulnerable (VU), Near Threatened (NT), Least Concern (LC), Data Deficient (DD), and Not Evaluated (NE). *, **, *** indicate the significance level of the difference in medians between the conservation category and all of the more threatened categories.

By contrast, there was little correlation between the median AIE of a species and its IUCN conservation status ($r^2 = 0.07, p = 0.3$). (See Figure 2.2b.) This supports the notion that while species sensitivity to climate change is at least partially reflected in IUCN conservation status, conservation status does not appear to account for exposure to climate change (Thuiller et al., 2005; Akçakaya et al., 2006; Hannah, 2011).

The correlation between IUCN conservation status and climate breadth suggests that climate breadth can be useful for identifying species that would be considered at-risk under IUCN criteria, while depending on considerably less data. The extent to which Red List status and climate breadth or AIE disagree is not an indication our metrics perform poorly: VU+ status does not imply low climate breadth or AIE, since there are many other reasons besides vulnerability to climate change why a species might be considered VU+; similarly, LC species with low climate breadth or AIE simply suggest that their LC designations do not adequately account for their climate change vulnerability.

We conclude that species with low climate breadth and high AIE that are categorized as DD or NE should be prioritized for a more detailed vulnerability assessment. Similarly, species with low climate breadth and high AIE that are categorized as LC should be considered as candidates for possible reclassification. It is also worth noting that out of the 32 species identified as most vulnerable using climate breadth and AIE, 18 of them are currently categorized as Data Deficient or Not Evaluated (see Table 2.3). Clearly, more effort and research is needed here.

2.2 *Foden et al.'s method*

To address the perceived shortcomings of the IUCN criteria in capturing the effects of climate change, a number of new methods for assessing species vulnerability have been recently proposed (Thomas et al., 2011; Young et al., 2012; Foden et al., 2013a). These methods tend to rely on expert opinion, however, and as such, struggle to assess species when little information is known about them. In contrast, climate breadth and index of exposure can objectively quantify species vulnerability to climate change while relying on relatively little species data, as we established in Chapter 1.

Foden et al. (2013a) developed a method for quantifying impacts of climate change that emphasized measuring the biological differences between species that can significantly affect their vulnerability. Using the framework in Figure 1.1, species vulnerability was assessed by separating vulnerability into three independent dimensions: sensitivity, exposure, and adaptive capacity, with each dimension composed of a specified set of traits; sensitivity, for example, was characterized by specialized habitat requirements, rarity, and environmental tolerances that are likely to be exceeded by climate change. Drawing on information available literature and expert opinion, if a species is judged as high risk in any one of these traits, the species is then categorized as high risk for that dimension. If a species is categorized as high risk in all three dimensions, then that species is considered highly vulnerable.

In a monumental undertaking, Foden *et al.* applied their methods to more than 16,000 species of birds, amphibians, and corals (Foden et al., 2013a). Of these 16,000+ species, 104 of them were also assessed in our study.

Although climate breadth only measures one sensitivity trait, we would expect it to correlate with Foden's sensitivity assessments, because any species with a low climate breadth should in theory have a narrow range of environmental tolerances, which would categorize it as highly sensitive. We might also expect the index of exposure to correlate with Foden's exposure assessments, although as we saw in Chapter 1, IE values are highly dependent on the future climate scenario used to calculate them; in Foden's study, exposure was assessed using projections under the more moderate A1B emissions scenario (Solomon, 2007), so we do not necessarily expect agreement between the two models. Additionally, Foden's climate change projections were based on an ensemble of four different global climate models, providing another source of potential disagreement.

To compare climate breadth with Foden's sensitivity, the median σ_c of each taxon was naively used as a break point; any species with a σ_c below the median of its taxon was said to have relatively high sensitivity, and species above the median relatively low sensitivity. A similar approach was used to split each taxon into two groups by AIE.

Species that were categorized as highly sensitive with climate breadth were very likely to be categorized as highly sensitive by Foden, with 95% agreement of bird species and 84% agreement of amphibian species (see Table 2.1). In contrast, many species that were identified as highly sensitive by Foden were not considered highly sensitive when using climate breadth. This is not a surprising result; many species traits that are not captured by climate breadth can lead to classification as highly sensitive using Foden's method. This suggests that although climate breadth can identify sensitive species effectively, it is important to consider other traits that affect sensitivity as well.

	Foden sensitivity		
	Birds	High	Low
σ_c	Low	20	1
	High	14	5

	Foden exposure		
	Birds	High	Low
AIE	High	16	4
	Low	15	5

	Foden sensitivity		
	Amphibians	High	Low
σ_c	Low	26	5
	High	17	14

	Foden exposure		
	Amphibians	High	Low
AIE	High	17	15
	Low	3	27

Table 2.1: Results of climate breadth (σ_c) and AIE models compared with Foden's methods. σ_c and AIE were delineated into groups above and below the median σ_c and AIE for each taxon. A low σ_c corresponds to high sensitivity and high σ_c to low sensitivity. Green indicates agreement between the two models and red indicates disagreement.

Results were more varied for AIE. There was little difference in AIE between Foden's high exposure and low exposure groups of birds, but a significant difference was observed between amphibian groups (Mann-Whitney $U = 701$, $n_1 = 20$, $n_2 = 42$, $p < 0.0001$) (see Figure 2.3b). One possible explanation for this disparity between taxa is that it is related to distribution size. The mean range size for the 62 amphibians 206,000 km^2, compared with 1,793,000 km^2 for the 42 birds; the larger range area in birds amounts to eight times more area at which the future climate models can be at odds with one another, leading to less agreement between the two methods.

Overall, five species of amphibians and one bird were notably categorized as highly sensitive using climate breadth but failed to meet Foden's sensitivity criteria (see Table 2.2). We believe these species should be considered as at high latent risk or highly vulnerable, depending on their exposure and adaptive capacity.

Species	Climate breadth	AIE	IUCN	Foden Sen.	Foden Exp.
Aneides lugubris	34.38	89.53	Least Concern	Low	Low
Dicamptodon ensatus	16.98	86.51	Near Threatened	Low	Low
Hydromantes brunus	10.01	98.88	Vulnerable	Low	High
Hydromantes shastae	14.48	97.62	Vulnerable	Low	High
Taricha rivularis	30.39	87.44	Least Concern	Low	Low
Numenius americanus	41.56	99.32	Least Concern	Low	High

Table 2.2: Six species categorized as sensitive using climate breadth, but not considered sensitive under Foden's criteria.

Foden's method takes into account a wide variety of traits and characteristics in order to determine species vulnerability. It is a labor-intensive metric due to this reliance on detailed species information. It gives coarse, qualitative results that are useful for categorization, but cannot be used to compare vulnerability within these categories. The spatial components used in this method are also reduced to simple categorization, and as such, offers no spatial results or insight for individual species. We believe Foden's method could be improved by incorporating climate breadth to account for aspects of sensitivity, and using AIE to determine exposure.

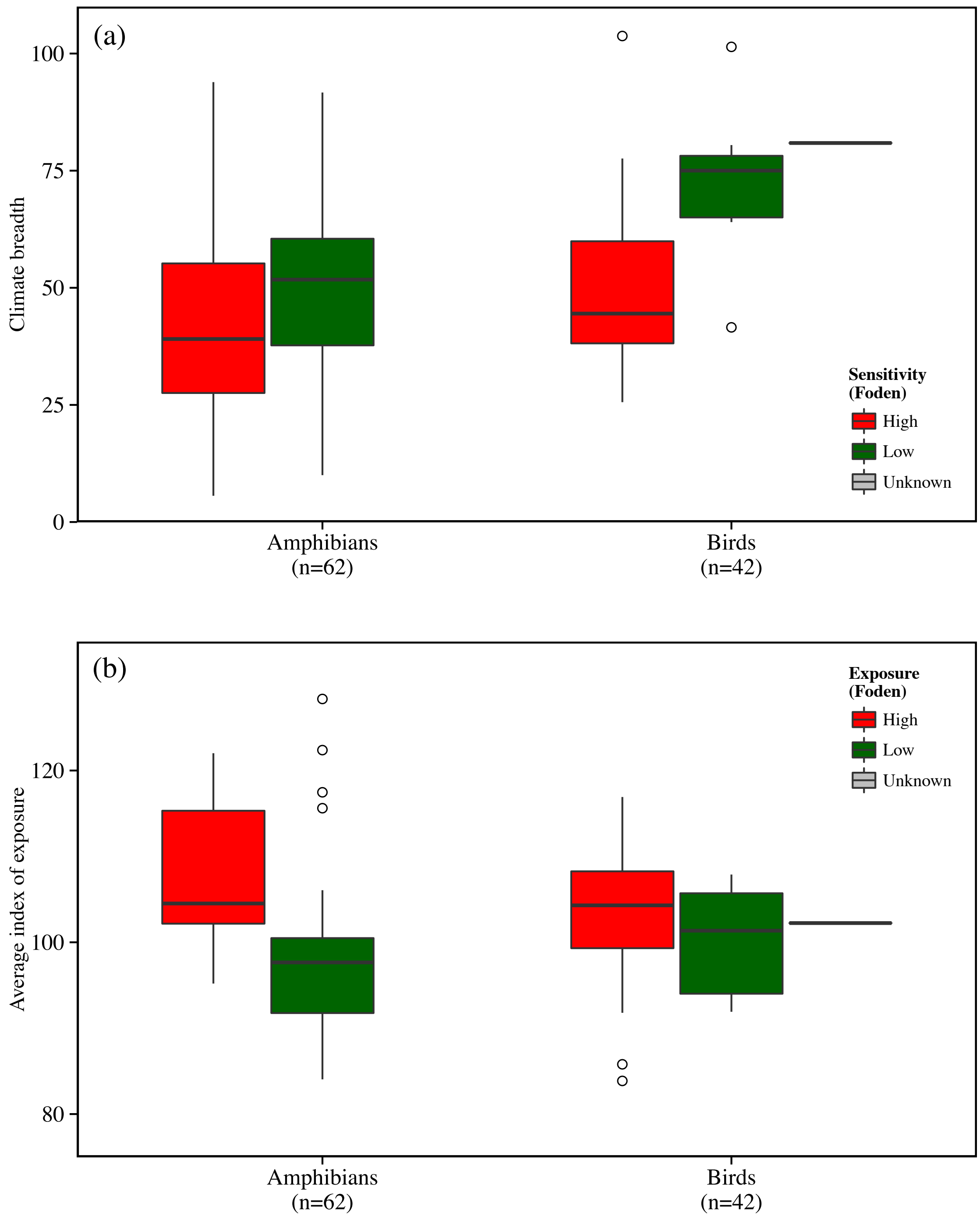

Figure 2.3: Boxplots of (a) climate breadths and (b) AIE by Foden's sensitivity classification.

2.3 *Climate change sensitivity database*

The Climate Change Sensitivity Database (CCSD) is a database created and maintained through a collaboration of universities, government, and non-gonvernment organizations (CCSD, 2014) as part of the Pacific Northwest Climate Change Vulnerability Assessment (Pacific Northwest Climate Change Vulnerability Assessment, 2014). The database contains detailed natural history information for Pacific Northwest species and uses expert opinion on physiology, dispersal ability, and other ecological factors to rank sensitivity to climate change. The database provides an index of sensitivity for each species that ranges from 0 to 100, and broadly classifies these values as low, medium, or high.

It is important to note a difference in terminology here. Up to now we have regarded sensitivity as but a single dimension of vulnerability. In the CCSD, the term sensitivity equates to what we have been calling vulnerability; the factors that are used to determine species sensitivity in the database include characteristics more properly categorized under what we have called adaptive capacity, such as the aforementioned dispersal ability. For the remainder of this section, when we use the term sensitivity, we will be using it in the same way as the sensitivity database.

Forty-seven of our 400 species are currently described and fully assessed in the CCSD. Each of these were placed into seven categories along a spectrum of sensitivity using the cumulative quartile ranks of climate breadth and AIE, as shown in Table 1.1. These were compared to the three categories of sensitivity (High, Medium, Low) found in the CCSD.

Results showed no clear relationship between the two methods (see Figure 2.4). There are several reasons why this might be the case. First, the CCSD by design is structured to accommodate assessments of regional subpopulations, and many species found in the database have not yet been evaluated at a range-wide level. The pgymy rabbit (*Brachylagus idahoensis*, $\sigma_c = 30.53$, AIE $= 108.4$), for example, has two entries in the database: one for the geographically distinct Columbia Basin population that is currently protected under the Endangered Species Act, and one for the rest of the population, which is generally not considered threatened (Siegel Thines et al., 2004) (see Figure 2.5). Thus, comparisons between subpopulations evaluated in the CCSD and whole populations evaluated using climate breadths and AIE may not be meaningful.

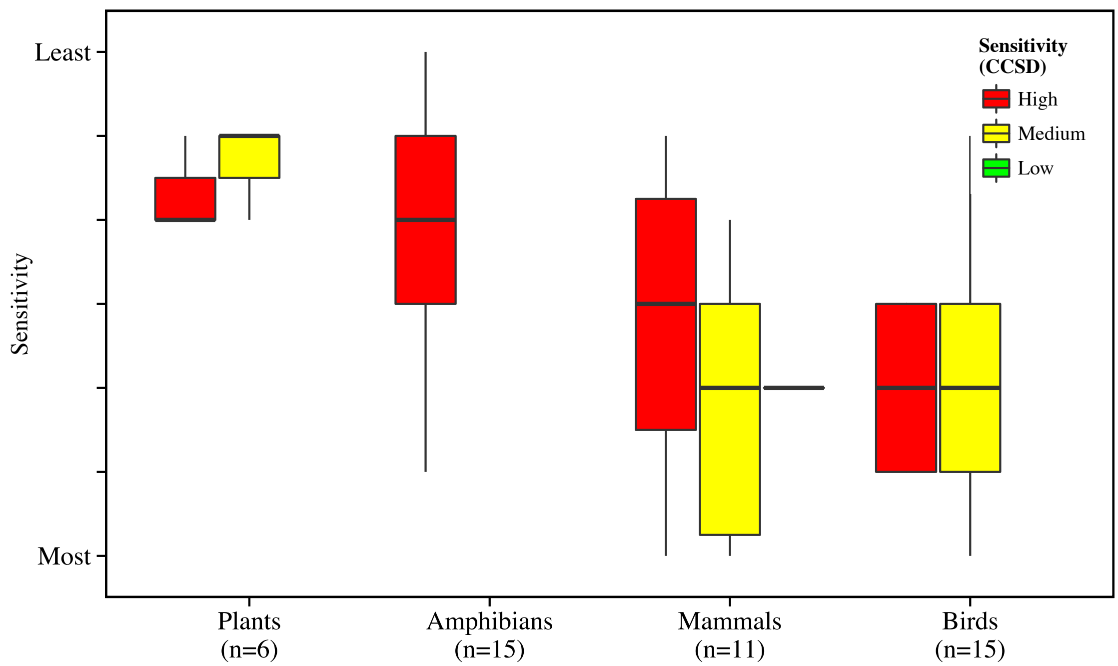

Figure 2.4: Boxplots of sensitivity scores by CCSD sensitivity category. The sensitivity scores are the cumulative quartile ranks of climate breadth and AIE, as in Table 1.1.

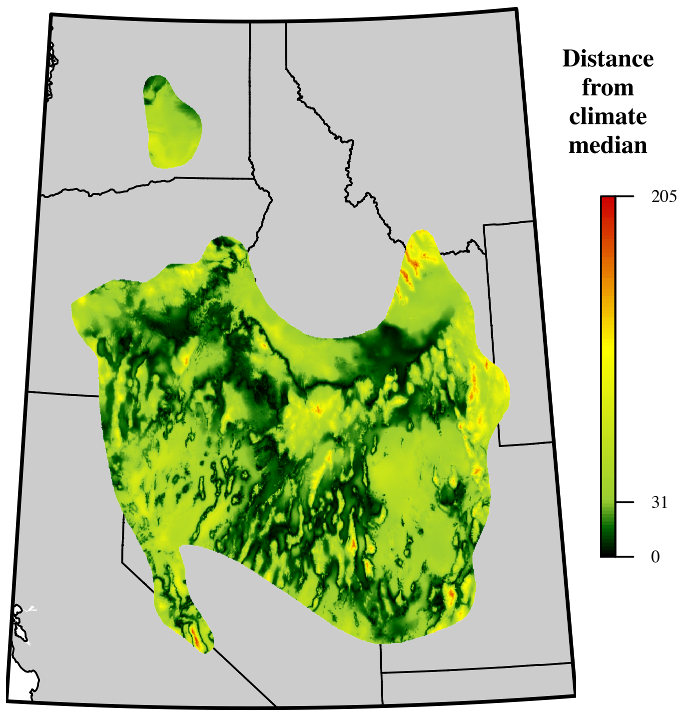

Figure 2.5: Climate breadth map of *Brachylagus idahoensis*, illustrating the geographically distinct subpopulation of Columbia Basin pygmy rabbits.

Second, the nine factors the CCSD uses to assess sensitivity focus mostly on species traits, life history, and ecological relationships, and less on future projections of changes in climate. Thus, the information captured in the index of exposure of a given species might not be reflected in its CCSD sensitivity at all. A more clear relationship emerges when CCSD sensitivity is compared to climate breadth alone (see Figure 2.6).

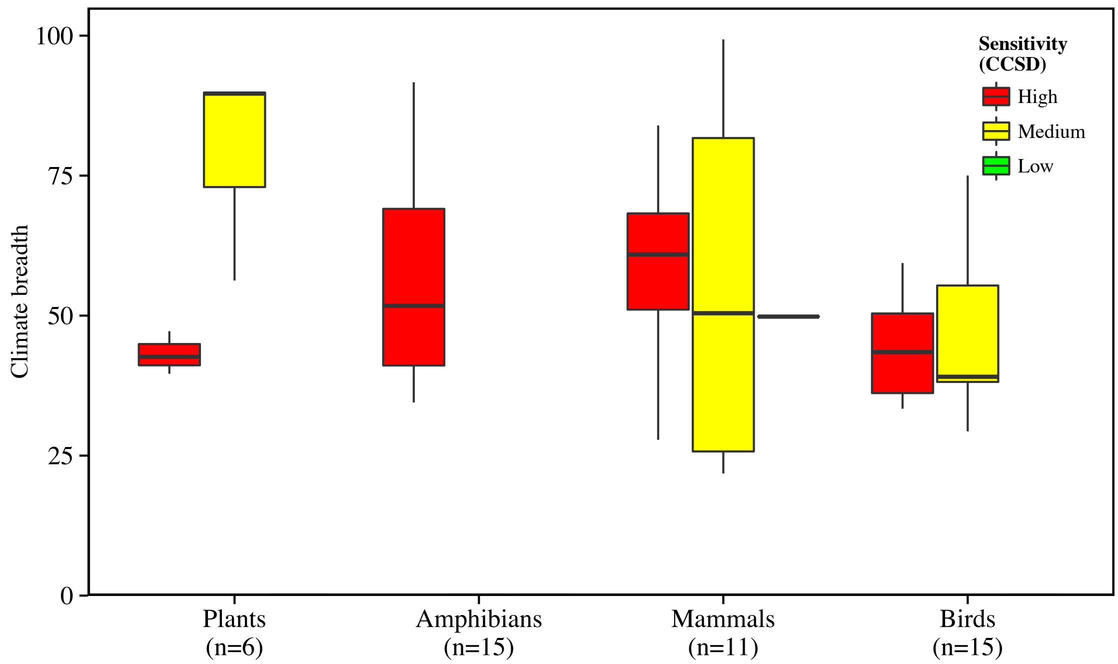

Figure 2.6: Boxplots of climate breadth by CCSD sensitivity category.

Finally, conclusions may be difficult to draw simply due to the small sample size alone. Out of the three assessment methods reviewed the CCSD had the fewest number of species in common with our original 400. It is worth noting that the CCSD is an ongoing collaboration, and species are undergoing continual evaluation and revision.

Despite the small sample size used for comparison, it seems clear that these two methods offer different insights from one another based on different considered information. This comparison highlights the importance of using a diverse variety of methods and information when assessing species vulnerability.

2.4 *Most vulnerable species*

Thrity-two of the 400 species considered in this study fell in both the lowest quartile of climate breadth and the highest quartile of AIE, and should be considered as highly vulnerable (see Table 2.3). Many of these species are already categorized as vulnerable by the IUCN or are otherwise in agreement with the other assessment methods we have explored. We will now briefly highlight some of the species in this study that we believe should be considered for reevaluation of conservation status based on our results. A comprehensive list of the results for all 400 species can be found in Appendix II.

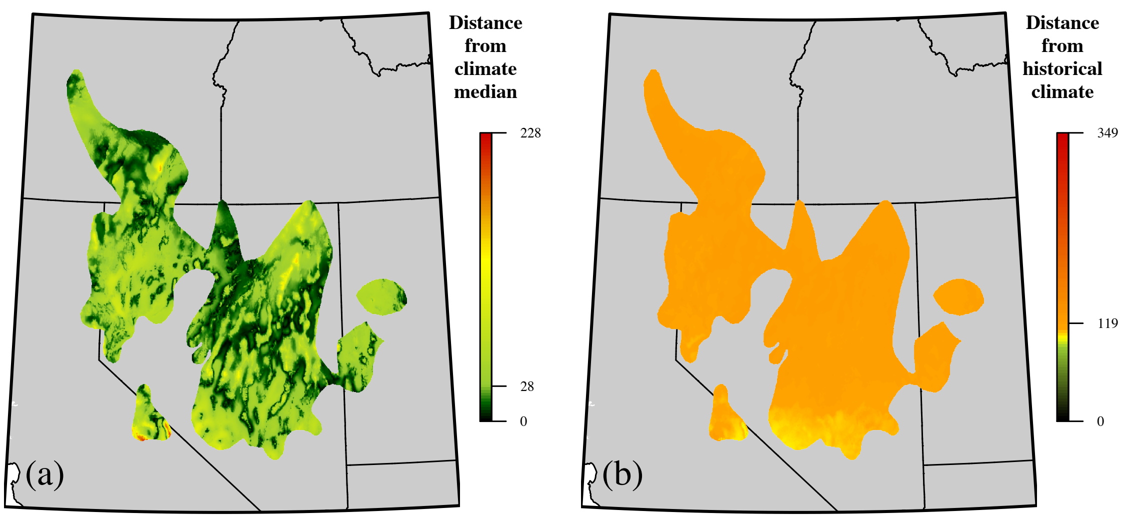

Figure 2.7: (a) Sensitivity and (b) exposure maps of *Microdipodops megacephalus* under the BCCR climate scenario.

The dark kangaroo mouse (*Microdipodops megacephalus*, $\sigma_c = 27.82$, AIE $= 109.3$, range area $\approx$ 345,000 km^2, IUCN status = LC) is a species of rodent native primarily to Nevada and Oregon. Despite its relatively broad distribution, this species is found in a very limited range of climate. Substantial changes in future climate are predicted within *M. megacephalus*'s habitat (see Figure 2.7). Cockrum's desert shrew (*Notiosorex cockrumi*, σ_c = 34.18, AIE = 121.9, range area $\approx$ 90,000 km^2, IUCN status = LC) is similarly assessed.

The Sonoran green toad (*Anaxyrus retiformis*, σ_c =21.30, AIE = 119.9, range area $\approx$ 71,000 km^2, IUCN status = LC) lives in the Southwestern desert and estivates the majority of the year, only emerging during brief periods of heavy rainfall (Sullivan et al., 1996). This extreme dependence on specific climatic conditions is reflected in its low climate breadth, and its high AIE suggests that it may face substantial future climate change.

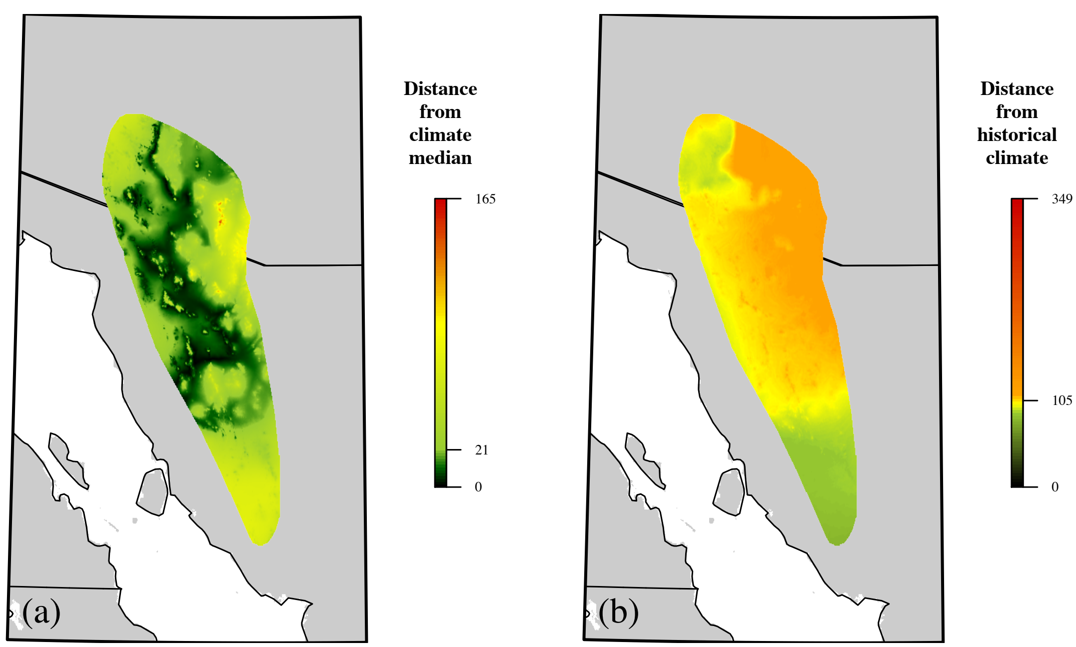

Figure 2.8: (a) Sensitivity and (b) exposure maps of *Anaxyrus retiformis* under the BCCR climate scenario.

Eight different slender salamanders (*Batrachoseps* spp.) had climate breadths in the bottom 20% of all species. Of these, three are expected to experience more climate change than average (*B. diabolicus*, $\sigma_c = 12.58$, AIE = 101.8, range area ≈ 3,000 km^2, IUCN status = DD; *B. gregarius*, $\sigma_c = 21.60$, AIE = 102.9, range area ≈ 11,000 km^2, IUCN status = LC; *B. regius*, $\sigma_c = 15.51$, AIE = 102.1, range area ≈ 200 km^2, IUCN status = VU).

The brown-capped rosy finch (*Leucosticte australis*, $\sigma_c = 33.99$, AIE = 106.7, range area ≈ 23,000 km^2, IUCN status = LC) and greater sage-grouse (*Centrocercus urophasianus*, $\sigma_c = 36.62$, AIE = 103.4, range area ≈ 2,240,000 km^2, IUCN status = NT) represent opposite ends of the spectrum for habitat size, but ranked comparably high in both sensitivity and exposure.

Most of the 145 plant species have not yet been evaluated (NE) by the IUCN. Many oaks (*Quercus* spp.) fared poorly in this study; ten had notably low sensitivity scores with significant changes in future habitat (mean $\sigma_c = 15.9 \pm 5.7$, mean AIE $= 114.4 \pm 6.3$, mean range area $\approx 32,000 \pm 33,000$ km^2). Only one of these is currently recognized as threatened (*Q. graciliformis*, $\sigma_c = 14.52$, AIE = 102.1, range area ≈ 600 km^2, IUCN status = CR). The Ajo Mountain scrub oak (*Q. ajoensis*, $\sigma_c = 10.29$, AIE = 110.1, range area ≈ 3000 km^2, IUCN status = NE) ranked even lower than *Q. graciliformis*, despite having a range five times as large.

Species	Taxon	Red List status	Range size	Climate breadth	AIE	IE CGCM3	IE CSIRO	IE BCCR
Anaxyrus nelsoni	Amphibian	Endangered	113	6.15	111.75	125.91	99.41	109.94
Anaxyrus retiformis	Amphibian	Least Concern	70843	21.30	119.93	132.87	122.25	104.65
Cercidium microphyllum	Plant	Not Evaluated	314336	31.34	115.75	114.84	114.62	117.79
Cynomys parvidens	Mammal	Endangered	12237	31.66	113.94	120.31	102.78	118.72
Dalea spinosa	Plant	Not Evaluated	148714	20.39	111.60	136.71	107.58	90.51
Fraxinus gooddingii	Plant	Not Evaluated	3290	29.28	124.62	133.19	126.42	114.24
Geomys arenarius	Mammal	Near Threatened	165720	23.00	112.64	104.79	115.30	117.82
Geomys knoxjonesi	Mammal	Least Concern	80420	15.24	109.85	94.57	109.46	125.53
Holacantha emoryi	Plant	Not Evaluated	122614	21.88	114.69	132.98	109.93	101.16
Lithobates lemosespinali	Amphibian	Data Deficient	110	25.55	128.72	140.82	138.14	107.19
Lithobates subaquavocalis	Amphibian	Critically Endangered	305	21.34	122.37	128.69	121.75	116.67
Microdipodops megacephalus	Mammal	Least Concern	344912	27.82	109.30	113.91	95.41	118.59
Peromyscus polius	Mammal	Near Threatened	31800	16.36	118.63	125.02	119.96	110.90
Pinus monophylla	Plant	Least Concern	112538	31.78	108.99	115.95	96.65	114.38
Pinus quadrifolia	Plant	Least Concern	7140	23.86	109.25	124.96	104.92	97.87
Platanus wrightii	Plant	Not Evaluated	144633	31.20	119.29	124.60	117.51	115.76
Populus hinckleyana	Plant	Not Evaluated	328	12.73	108.60	98.97	111.16	115.68
Quercus ajoensis	Plant	Not Evaluated	2753	10.29	110.10	130.93	107.15	92.21
Quercus dunnii	Plant	Not Evaluated	30843	28.79	114.76	122.56	109.45	112.28
Quercus hypoleucoides	Plant	Not Evaluated	42987	29.41	118.52	123.49	119.05	113.03
Quercus oblongifolia	Plant	Not Evaluated	28917	26.59	122.37	129.45	122.19	115.47
Quercus toumeyi	Plant	Least Concern	7412	29.31	120.63	126.46	119.78	115.63
Rhus choriophylla	Plant	Not Evaluated	18679	26.35	121.89	128.46	121.31	115.88
Sorex arizonae	Mammal	Least Concern	84756	25.96	120.18	125.89	119.16	115.51
Spermophilus mollis	Mammal	Least Concern	644038	29.50	109.34	114.19	96.66	117.18
Sylvilagus cognatus	Mammal	Data Deficient	5837	12.22	117.46	109.72	117.41	125.25
Thomomys townsendii	Mammal	Least Concern	176744	23.94	109.15	111.88	96.88	118.70
Vauquelinia pauciflora	Plant	Not Evaluated	279	13.34	118.07	123.51	115.85	114.85
Yucca elata	Plant	Not Evaluated	349615	28.65	114.63	112.35	115.35	116.20
Yucca faxoniana	Plant	Not Evaluated	8338	11.07	110.12	101.56	113.41	115.39
Yucca schottii	Plant	Not Evaluated	13945	26.41	121.13	127.51	120.37	115.52
Yucca torreyi	Plant	Not Evaluated	272518	29.39	109.12	103.48	108.87	115.01

Table 2.3: A list of the 32 most vulnerable species in our study, comprising the 1st quartile of climate breadths and the 4th quartile of AIE.

2.5 Discussion

Each of the three methods examined in this chapter relied heavily on intimate, detailed knowledge of a species in order to make an assessment of different aspects of species vulnerability. This is both a blessing and a curse; it is obviously important to base any assessment on as much information as is available to be as thorough and comprehensive as possible, but this limits our ability to draw conclusions about a species' conservation status when little is known about it. As we have seen, if a species has a low climate breadth and a high index of exposure, it is a very strong indicator that, by most definitions, the species meets at least some of the important criteria for vulnerability. This provides us with a simple but powerful tool with which to approach species of unknown status. Our method is not intended to replace other more informed models or ones that take detailed life history into account; rather it is intended as a form of triage, a tool that can rapidly and objectively identify species of potential vulnerability when little is known about them.

Our comparison lent credence to the assertion that the IUCN criteria for vulnerability do not adequately account for the effects of climate change, but it also offers a solution. An internationally standardized dataset of significant climate variables could easily be constructed and used to calculate indices of exposure for any future climate scenario in a manner that is internally consistent for the entire globe, and hence, all species. Regardless of the inherent uncertainty in future predictions, potential exposure to climate change is readily quantifiable, and must be considered in species conservation status.

We also suggested how our methods could be incorporated into other vulnerability assessment methods to gain a more objective measure of a species' climatic niche and the climate change it will be exposed to. Going forward, we sincerely hope to see this occur; both climate breadth and the index of exposure are designed to be extremely flexible and adaptable, and work in concert with or augment other methods.

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Appendix I

BIOCLIMATE VARIABLES

The table below lists the bioclimatic variables used in this study.

Annual variables	
MAT	mean annual temperature (°C)
MWMT	mean warmest month temperature (°C)
MCMT	mean coldest month temperature (°C)
TD	temperature difference between MWMT and MCMT, or continentality (°C)
MAP	mean annual precipitation (mm)
MSP	mean summer (May to Sept.) precipitation (mm)
AHM	annual heat:moisture index ((MAT+10)/(MAP/1000))
SHM	summer heat:moisture index ((MWMT)/(MSP/1000))
DD<0	degree-days below 0°C, chilling degree-days
DD>5	degree-days above 5°C, growing degree-days
DD<18	degree-days below 18°C, cooling degree-days
DD>18	degree-days above 18°C, heating degree-days
NFFD	the number of frost-free days
FFP	frost-free period
bFFP	the Julian date on which FFP begins
eFFP	the Julian date on which FFP ends
PAS	precipitation as snow (mm) between August in previous year and July in current year
EMT	extreme minimum temperature over 30 years
Eref	Hargreaves reference evaporation
CMD	Hargreaves climatic moisture deficit
Seasonal variables	
TAV_{wt}	winter (Dec.(prev. yr) - Feb.) mean temperature (°C)
TAV_{sp}	spring (Mar. - May) mean temperature (°C)
TAV_{sm}	summer (Jun. - Aug.) mean temperature (°C)
TAV_{at}	autumn (Sep. - Nov.) mean temperature (°C)
$TMAX_{wt}$	winter mean maximum temperature (°C)
$TMAX_{sp}$	spring mean maximum temperature (°C)
$TMAX_{sm}$	summer mean maximum temperature (°C)
$TMAX_{at}$	autumn mean maximum temperature (°C)
$TMIN_{wt}$	winter mean minimum temperature (°C)
$TMIN_{sp}$	spring mean minimum temperature (°C)
$TMIN_{sm}$	summer mean minimum temperature (°C)
$TMIN_{at}$	autumn mean minimum temperature (°C)
PPT_{wt}	winter precipitation (mm)
PPT_{sp}	spring precipitation (mm)
PPT_{sm}	summer precipitation (mm)
PPT_{at}	autumn precipitation (mm)
Monthly variables	
$TMAX_{07}$	July maximum mean temperature (°C)
$TMIN_{01}$	January minimum mean temperature (°C)
PPT_{04}	April precipitation (mm)
PPT_{12}	December precipitation (mm)

Appendix II

SPECIES TABLE

The following table gives the results of all 400 species in this study. The climate breadths and indices of exposure (IE) of the three future climate scenarios listed were calculated at a resolution of 1 km^2. The range size represents the number of cells with the species present at this resolution. Please note that some species have undergone recent taxonomic reclassification, and their binomial names may have been changed to reflect this. The names listed below are as they were found in the IUCN and USGS databases at the time of this study (IUCN, 2014; U.S. Geological Survey, 2014).

Amphibians

Species	Red List status	Range size	Climate breadth	AIE	IE CGCM3	IE CSIRO	IE BCCR
Ambystoma californiense	Vulnerable	25570	22.89	90.82	99.22	84.65	88.59
Ambystoma gracile	Least Concern	603269	105.21	96.92	109.14	89.43	92.19
Ambystoma macrodactylum	Least Concern	2596310	76.73	95.21	101.98	94.43	89.22
Anaxyrus baxteri	Extinct in the Wild	164	13.97	104.89	103.32	100.90	110.46
Anaxyrus californicus	Endangered	78744	42.87	106.22	123.89	104.85	89.94
Anaxyrus canorus	Endangered	15188	48.28	100.48	102.40	88.22	110.81
Anaxyrus exsul	Vulnerable	153	34.68	100.47	109.18	90.72	101.51
Anaxyrus microscaphus	Least Concern	344107	65.95	114.09	119.38	108.49	114.40
Anaxyrus nelsoni	Endangered	113	6.15	111.75	125.91	99.41	109.94
Anaxyrus retiformis	Least Concern	70843	21.30	119.93	132.87	122.25	104.65
Aneides flavipunctatus	Near Threatened	72516	51.96	89.97	93.69	82.99	93.22
Aneides hardii	Least Concern	41205	42.89	114.98	105.48	117.45	122.00
Aneides lugubris	Least Concern	155612	37.73	89.47	97.05	85.59	85.76
Aneides vagrans	Near Threatened	86904	103.05	93.53	105.03	87.92	87.66
Ascaphus montanus	Least Concern	402822	48.14	102.22	104.40	98.81	103.47
Ascaphus truei	Least Concern	518019	100.62	97.34	108.95	89.22	93.85
Batrachoseps attenuatus	Least Concern	81669	50.99	89.21	94.24	82.66	90.73
Batrachoseps campi	Endangered	485	45.33	100.03	107.81	91.40	100.87
Batrachoseps diabolicus	Data Deficient	2975	12.58	101.81	105.99	91.91	107.51
Batrachoseps gabrieli	Data Deficient	804	32.35	102.84	108.61	100.71	99.20
Batrachoseps gavilanensis	Least Concern	16389	19.94	86.71	98.71	87.19	74.22
Batrachoseps gregarius	Least Concern	11365	21.60	102.93	108.61	96.54	103.62
Batrachoseps incognitus	Data Deficient	1168	22.26	82.95	96.39	85.74	66.73
Batrachoseps kawia	Data Deficient	2221	85.84	98.55	101.61	89.56	104.49
Batrachoseps luciae	Least Concern	2300	28.10	85.35	94.27	80.58	81.19
Batrachoseps major	Least Concern	38061	21.13	100.05	113.41	99.93	86.81
Batrachoseps minor	Data Deficient	1622	17.54	84.28	96.43	87.60	68.80
Batrachoseps nigriventris	Least Concern	34984	30.80	88.38	97.62	90.10	77.40
Batrachoseps regius	Vulnerable	231	15.51	102.10	105.41	95.42	105.47
Batrachoseps relictus	Data Deficient	1398	29.66	100.01	106.50	92.06	101.46

Amphibians

Species	Red List status	Range size	Climate breadth	AIE	IE CGCM3	IE CSIRO	IE BCCR
Batrachoseps robustus	Near Threatened	2085	43.87	98.71	106.94	91.77	97.43
Batrachoseps simatus	Vulnerable	255	38.85	100.43	107.88	93.97	99.43
Batrachoseps stebbinsi	Vulnerable	504	36.96	97.57	107.35	94.69	90.68
Batrachoseps wrighti	Vulnerable	18994	42.06	99.29	108.35	87.03	102.49
Dicamptodon aterrimus	Least Concern	89099	46.60	105.94	108.31	100.50	109.03
Dicamptodon copei	Least Concern	43928	47.97	102.31	119.83	92.58	94.53
Dicamptodon ensatus	Near Threatened	16655	18.64	86.31	91.35	79.06	88.53
Dicamptodon tenebrosus	Least Concern	274168	61.70	95.83	102.77	87.19	97.52
Ensatina eschscholtzii	Least Concern	501602	90.15	94.99	101.72	87.70	95.56
Hydromantes brunus	Vulnerable	181	10.98	98.66	103.34	91.36	101.27
Hydromantes shastae	Vulnerable	655	15.90	97.30	99.89	87.54	104.46
Hyla wrightorum	Least Concern	215080	52.22	115.53	116.93	114.77	114.89
Incilius alvarius	Least Concern	489387	55.57	116.61	128.57	115.13	106.13
Lithobates lemosespinali	Data Deficient	110	25.55	128.72	140.82	138.14	107.19
Lithobates onca	Endangered	15674	65.98	115.90	129.25	104.23	114.23
Lithobates subaquavocalis	Critically Endangered	305	21.34	122.37	128.69	121.75	116.67
Lithobates tarahumarae	Vulnerable	129174	65.59	122.19	132.21	125.44	108.91
Lithobates yavapaiensis	Least Concern	338333	76.63	117.39	124.26	114.04	113.87
Plethodon asupak	Vulnerable	107	17.47	89.95	91.48	80.93	97.45
Plethodon dunni	Least Concern	119322	50.26	95.44	102.93	87.26	96.13
Plethodon elongatus	Near Threatened	36372	58.57	91.45	95.85	85.16	93.35
Plethodon idahoensis	Least Concern	141329	44.07	102.75	105.12	99.55	103.59
Plethodon larselli	Near Threatened	26232	91.51	100.35	112.75	88.46	99.83
Plethodon neomexicanus	Near Threatened	5404	44.83	115.70	110.85	115.05	121.18
Plethodon stormi	Endangered	3302	37.87	88.63	89.59	80.67	95.63
Plethodon vandykei	Least Concern	32135	57.83	102.59	120.11	92.15	95.51
Plethodon vehiculum	Least Concern	282057	76.08	99.01	111.37	91.25	94.41
Pseudacris cadaverina	Least Concern	88762	38.30	99.70	112.27	99.03	87.79
Pseudacris regilla	Least Concern	2460128	81.90	101.50	106.99	94.41	103.09
Rana aurora	Least Concern	368407	80.56	97.16	108.67	89.46	93.34
Rana boylii	Near Threatened	296861	71.03	94.22	97.80	85.76	99.10
Rana cascadae	Near Threatened	188029	81.71	98.11	106.33	88.07	99.92
Rana draytonii	Vulnerable	199900	39.83	92.78	100.23	89.94	88.17
Rana muscosa	Endangered	23016	98.21	98.73	105.09	91.57	99.51
Rana pretiosa	Vulnerable	101761	68.43	97.50	101.06	86.35	105.08
Rhyacotriton cascadae	Near Threatened	40042	45.04	100.45	111.86	89.30	100.20
Rhyacotriton kezeri	Near Threatened	23572	56.79	97.62	110.51	89.50	92.85
Rhyacotriton olympicus	Vulnerable	27498	58.86	100.94	115.46	94.02	93.34
Rhyacotriton variegatus	Least Concern	74887	45.16	91.95	97.32	85.56	92.98
Spea intermontana	Least Concern	1553136	40.07	108.02	111.25	97.82	114.99
Taricha rivularis	Least Concern	21258	33.35	87.26	91.85	81.09	88.85
Taricha sierra	Least Concern	41370	53.03	101.66	105.76	91.73	107.50
Taricha torosa	Least Concern	70996	31.70	87.39	94.72	83.42	84.04

Birds

Species	Red List status	Range size	Climate breadth	AIE	IE CGCM3	IE CSIRO	IE BCCR
Agelaius tricolor	Endangered	163753	32.19	91.76	99.60	88.77	86.90
Amphispiza belli	Least Concern	1643440	45.99	108.27	112.28	97.98	114.54
Baelophus ridgwayi	Least Concern	1559346	40.12	110.63	113.88	101.54	116.47
Buteo regalis	Least Concern	3698411	41.88	104.14	102.58	100.03	109.81
Calcarius mccownii	Least Concern	1176516	28.08	97.27	93.79	99.00	99.04
Callipepla californica	Least Concern	1645591	88.79	100.71	103.47	92.88	101.64
Callipepla gambelii	Least Concern	755708	84.99	115.66	123.48	110.69	112.82
Calypte anna	Least Concern	722020	88.31	99.18	107.65	92.84	97.05

Birds

Species	Red List status	Range size	Climate breadth	AIE	IE CGCM3	IE CSIRO	IE BCCR
Calypte costae	Least Concern	742996	54.36	110.43	127.28	106.68	97.31
Carduelis lawrencei	Least Concern	197989	41.85	93.59	103.09	92.21	85.48
Carpodacus cassinii	Near Threatened	2400211	57.24	104.86	106.24	97.62	110.72
Centrocercus urophasianus	Near Threatened	2244312	36.62	103.39	103.10	97.83	109.23
Charadrius montanus	Near Threatened	1046343	37.58	102.63	100.71	98.57	108.62
Dendroica nigrescens	Least Concern	2729356	66.78	107.83	111.68	97.81	114.00
Dendroica occidentalis	Least Concern	523620	83.27	95.53	112.67	86.85	98.89
Empidonax difficilis	Least Concern	1517738	111.32	94.49	103.91	92.94	86.61
Empidonax oberholseri	Least Concern	4339282	68.79	101.60	104.29	96.67	103.84
Empidonax wrightii	Least Concern	1737995	39.77	109.08	111.83	99.06	116.34
Falco mexicanus	Least Concern	5800622	68.76	104.18	105.73	99.31	107.49
Gymnorhinus cyanocephalus	Vulnerable	2433274	42.90	107.63	109.52	99.27	114.11
Icterus cucullatus	Least Concern	5462580	72.44	105.07	105.16	98.59	111.45
Larus occidentalis	Least Concern	50381	70.26	85.79	93.12	83.65	80.59
Leucosticte atrata	Least Concern	220810	49.46	98.24	96.65	97.78	100.29
Leucosticte australis	Least Concern	23149	33.99	106.74	109.51	98.91	111.79
Melanerpes lewis	Least Concern	3304321	70.12	103.99	106.00	97.02	108.94
Nucifraga columbiana	Least Concern	3614915	65.18	103.69	105.62	97.43	108.03
Numenius americanus	Least Concern	3358659	45.61	101.50	97.01	97.84	105.48
Oreoscoptes montanus	Least Concern	2748047	42.44	105.61	107.67	96.91	112.24
Oreortyx pictus	Least Concern	530347	82.33	98.42	103.77	88.51	103.00
Pica nuttalli	Near Threatened	122240	31.90	93.84	99.16	87.67	94.70
Picoides albolarvatus	Least Concern	789918	60.78	101.07	105.79	91.48	105.93
Picoides nuttallii	Least Concern	268586	48.20	91.80	98.77	86.68	89.95
Pipilo aberti	Least Concern	238844	66.90	116.82	126.21	111.63	112.63
Pipilo chlorurus	Least Concern	2636663	47.59	107.62	109.55	98.75	114.55
Selasphorus sasin	Least Concern	45689	47.11	83.77	89.68	79.72	81.92
Sphyrapicus nuchalis	Least Concern	3318154	60.42	105.08	106.72	98.60	109.93
Sphyrapicus ruber	Least Concern	1765965	113.86	92.35	103.61	93.91	79.52
Sphyrapicus thyroideus	Least Concern	995213	63.46	107.64	109.18	100.98	112.75
Spizella breweri	Least Concern	5266998	61.92	100.36	101.79	97.04	102.23
Stellula calliope	Least Concern	2002083	65.97	99.43	102.37	94.80	101.13
Toxostoma bendirei	Vulnerable	1091966	85.16	114.60	120.53	108.91	114.37
Toxostoma lecontei	Least Concern	351426	43.64	108.82	129.34	99.77	97.33

Mammals

Species	Red List status	Range size	Climate breadth	AIE	IE CGCM3	IE CSIRO	IE BCCR
Ammospermophilus harrisii	Least Concern	372278	59.08	118.46	128.30	116.12	110.98
Ammospermophilus interpres	Least Concern	414602	39.62	106.41	99.88	103.53	115.81
Ammospermophilus leucurus	Least Concern	1424099	45.44	109.87	115.68	98.66	115.26
Aplodontia rufa	Least Concern	400079	75.06	96.75	104.53	88.65	97.08
Arborimus albipes	Least Concern	124315	44.16	93.92	100.12	86.69	94.96
Arborimus longicaudus	Near Threatened	87020	47.56	94.49	101.02	86.96	95.47
Arborimus pomo	Near Threatened	33248	34.85	88.90	92.37	83.54	90.80
Brachylagus idahoensis	Least Concern	759669	30.53	108.45	111.29	96.59	117.47
Chaetodipus baileyi	Least Concern	384740	51.03	117.69	129.07	116.81	107.17
Chaetodipus californicus	Least Concern	152056	39.32	91.57	101.56	91.62	81.54
Chaetodipus fallax	Least Concern	62979	34.81	103.56	122.59	103.22	84.88
Chaetodipus formosus	Least Concern	468153	78.56	108.38	119.99	96.72	108.43
Chaetodipus goldmani	Near Threatened	76630	28.66	105.52	127.65	112.72	76.21
Chaetodipus intermedius	Least Concern	705140	44.36	116.64	119.09	115.66	115.17
Chaetodipus penicillatus	Least Concern	544445	56.21	115.61	128.83	113.21	104.79
Cratogeomys castanops	Least Concern	870475	46.61	108.11	100.70	106.24	117.40
Cynomys gunnisoni	Least Concern	444730	41.09	113.03	113.30	109.48	116.32

Mammals

Species	Red List status	Range size	Climate breadth	AIE	IE CGCM3	IE CSIRO	IE BCCR
Cynomys leucurus	Least Concern	419107	37.11	104.70	103.33	100.20	110.57
Cynomys parvidens	Endangered	12237	31.66	113.94	120.31	102.78	118.72
Dipodomys agilis	Least Concern	54608	44.27	95.21	104.78	94.49	86.36
Dipodomys californicus	Least Concern	131503	70.76	94.08	96.08	83.56	102.60
Dipodomys deserti	Least Concern	435520	55.08	110.90	129.11	100.67	102.93
Dipodomys ingens	Endangered	9751	14.96	89.54	101.83	91.66	75.14
Dipodomys microps	Least Concern	591430	32.33	109.53	115.43	96.10	117.07
Dipodomys nitratoides	Vulnerable	16224	12.10	92.87	105.18	94.86	78.58
Dipodomys panamintinus	Least Concern	88624	90.36	100.90	107.93	92.23	102.54
Dipodomys simulans	Least Concern	127747	50.09	101.75	119.03	102.25	83.97
Dipodomys stephensi	Endangered	4109	10.41	101.63	114.24	100.83	89.84
Dipodomys venustus	Least Concern	23585	22.56	82.25	91.77	79.03	75.96
Euderma maculatum	Least Concern	3154211	71.69	109.28	111.90	101.75	114.20
Geomys arenarius	Near Threatened	165720	23.00	112.64	104.79	115.30	117.82
Geomys knoxjonesi	Least Concern	80420	15.24	109.85	94.57	109.46	125.53
Lemmiscus curtatus	Least Concern	2701261	41.61	101.59	100.39	97.94	106.43
Marmota flaviventris	Least Concern	2750943	42.48	103.71	105.14	97.40	108.58
Marmota olympus	Least Concern	9263	69.16	106.89	127.07	101.07	92.55
Marmota vancouverensis	Critically Endangered	11884	72.02	105.93	126.66	96.87	94.26
Microdipodops megacephalus	Least Concern	344912	27.82	109.30	113.91	95.41	118.59
Microdipodops pallidus	Least Concern	46370	17.77	107.06	114.48	94.80	111.90
Microtus californicus	Least Concern	419870	57.15	94.23	100.25	88.43	94.00
Microtus canicaudus	Least Concern	14634	9.63	95.13	100.70	87.34	97.34
Microtus montanus	Least Concern	2296794	46.41	105.03	106.49	96.94	111.67
Microtus oregoni	Least Concern	339809	66.34	96.89	106.02	88.01	96.63
Microtus richardsoni	Least Concern	1447969	66.56	99.58	102.07	96.53	100.13
Microtus townsendii	Least Concern	354209	70.06	96.91	106.32	88.35	96.07
Myodes californicus	Least Concern	315695	71.59	95.37	98.72	85.85	101.53
Myotis evotis	Least Concern	5121014	68.52	100.90	103.82	96.50	102.38
Myotis keenii	Least Concern	195490	92.15	98.79	119.52	91.87	84.97
Neotoma albigula	Least Concern	1148450	90.26	116.65	123.16	114.33	112.44
Neotoma devia	Least Concern	104124	51.95	113.72	126.05	106.15	108.95
Neotoma fuscipes	Least Concern	262060	73.95	93.49	97.62	85.58	97.25
Neotoma lepida	Least Concern	1404990	75.18	109.01	116.81	97.50	112.71
Neotoma macrotis	Least Concern	228816	63.04	98.24	106.33	92.67	95.71
Neotoma stephensi	Least Concern	322684	37.62	113.27	114.61	109.72	115.49
Neurotrichus gibbsii	Least Concern	360128	65.44	96.11	104.63	87.95	95.76
Notiosorex cockrumi	Least Concern	90138	34.18	121.90	129.37	122.04	114.30
Ochotona princeps	Least Concern	1598157	64.56	99.43	102.19	95.89	100.20
Onychomys torridus	Least Concern	1079034	85.23	111.36	123.90	103.78	106.41
Ovis canadensis	Least Concern	823174	109.02	103.80	109.42	98.44	103.52
Perognathus alticolus	Endangered	1467	28.75	97.29	106.72	96.84	88.31
Perognathus amplus	Least Concern	170190	42.92	118.40	128.42	115.66	111.13
Perognathus inornatus	Least Concern	107350	23.73	94.61	102.30	90.54	90.99
Perognathus longimembris	Least Concern	763138	78.33	107.56	116.00	96.24	110.45
Perognathus parvus	Least Concern	1435813	39.02	107.51	110.91	96.57	115.05
Peromyscus californicus	Least Concern	186873	40.39	95.78	105.84	94.32	87.18
Peromyscus crinitus	Least Concern	1365425	43.36	109.47	115.23	97.66	115.51
Peromyscus fraterculus	Least Concern	186452	44.57	103.74	125.43	104.68	81.10
Peromyscus hooperi	Least Concern	24621	20.14	91.86	94.91	84.40	96.28
Peromyscus keeni	Least Concern	405809	99.00	101.02	125.54	96.44	81.07
Peromyscus nasutus	Least Concern	805586	62.54	112.47	108.04	111.49	117.88
Peromyscus polius	Near Threatened	31800	16.36	118.63	125.02	119.96	110.90
Phenacomys intermedius	Least Concern	912178	73.73	99.48	105.16	96.90	96.38
Reithrodontomys burti	Data Deficient	67544	21.26	104.98	124.97	108.65	81.32

Mammals

Species	Red List status	Range size	Climate breadth	AIE	IE CGCM3	IE CSIRO	IE BCCR
Scapanus latimanus	Least Concern	484873	85.19	96.33	100.56	88.21	100.23
Scapanus orarius	Least Concern	582623	82.29	99.76	107.64	91.24	100.41
Scapanus townsendii	Least Concern	193219	55.84	97.79	107.90	89.83	95.64
Sciurus arizonensis	Data Deficient	54756	50.72	116.23	119.69	113.16	115.85
Sciurus griseus	Least Concern	575634	81.67	96.64	102.92	88.01	98.99
Sigmodon ochrognathus	Least Concern	591311	35.20	116.30	121.03	116.77	111.10
Sorex arizonae	Least Concern	84756	25.96	120.18	125.89	119.16	115.51
Sorex bairdi	Least Concern	59882	65.91	99.02	110.02	89.31	97.73
Sorex bendirii	Least Concern	339111	67.07	96.79	105.18	87.70	97.47
Sorex lyelli	Least Concern	4562	36.90	100.51	103.38	88.53	109.64
Sorex merriami	Least Concern	2796061	37.51	106.74	108.68	98.41	113.11
Sorex nanus	Least Concern	1525516	41.78	106.81	106.71	101.08	112.64
Sorex neomexicanus	Data Deficient	18944	51.64	115.36	105.78	117.87	122.42
Sorex ornatus	Least Concern	275570	38.40	95.30	103.75	92.17	89.98
Sorex pacificus	Least Concern	94022	56.68	95.56	100.95	86.50	99.24
Sorex preblei	Least Concern	1087548	40.59	103.78	104.28	96.68	110.39
Sorex rohweri	Least Concern	41092	63.02	99.57	112.65	92.36	93.69
Sorex sonomae	Least Concern	224057	64.84	92.79	96.52	84.65	97.21
Sorex tenellus	Least Concern	96063	64.18	104.66	115.01	93.35	105.61
Sorex trowbridgii	Least Concern	598525	82.22	95.99	102.47	87.79	97.71
Sorex vagrans	Least Concern	1599054	66.61	102.13	106.03	95.16	105.19
Spermophilus armatus	Least Concern	280538	49.74	101.92	99.18	100.92	105.64
Spermophilus atricapillus	Endangered	5573	17.14	91.94	113.32	95.98	66.52
Spermophilus beecheyi	Least Concern	692730	89.58	95.81	101.64	87.95	97.85
Spermophilus beldingi	Least Concern	528574	31.11	106.11	108.64	92.83	116.87
Spermophilus brunneus	Endangered	2090	12.90	106.12	109.43	96.94	112.00
Spermophilus canus	Least Concern	340541	26.88	107.60	110.05	93.86	118.89
Spermophilus columbianus	Least Concern	939806	56.97	97.69	100.71	96.00	96.36
Spermophilus elegans	Least Concern	451455	32.35	101.26	99.16	97.72	106.88
Spermophilus lateralis	Least Concern	2717986	62.37	104.76	106.28	97.04	110.97
Spermophilus madrensis	Near Threatened	63666	34.38	124.98	135.50	131.23	108.21
Spermophilus mohavensis	Vulnerable	29394	18.63	100.08	118.19	92.84	89.21
Spermophilus mollis	Least Concern	644038	29.50	109.34	114.19	96.66	117.18
Spermophilus saturatus	Least Concern	130049	78.10	100.76	112.59	93.30	96.39
Spermophilus tereticaudus	Least Concern	429034	43.51	113.63	130.41	108.61	101.88
Spermophilus townsendii	Vulnerable	18969	23.26	103.47	112.38	91.52	106.51
Spermophilus washingtoni	Near Threatened	29209	15.76	107.12	112.81	98.64	109.91
Sylvilagus cognatus	Data Deficient	5837	12.22	117.46	109.72	117.41	125.25
Sylvilagus nuttallii	Least Concern	3280618	42.84	104.76	105.51	98.20	110.55
Sylvilagus robustus	Endangered	51299	31.43	107.99	98.81	108.65	116.51
Tamias alpinus	Least Concern	12909	55.61	99.08	101.84	89.11	106.28
Tamias amoenus	Least Concern	1841409	61.06	100.79	103.34	95.08	103.94
Tamias canipes	Least Concern	26180	49.53	112.68	102.60	116.13	119.32
Tamias cinereicollis	Least Concern	103760	51.33	115.46	114.80	113.53	118.04
Tamias merriami	Least Concern	103365	51.91	93.86	102.54	90.55	88.49
Tamias obscurus	Least Concern	18664	43.48	107.66	122.11	103.40	97.48
Tamias ochrogenys	Least Concern	14307	30.05	85.92	90.64	80.21	86.91
Tamias palmeri	Endangered	440	22.68	102.78	112.95	93.16	102.24
Tamias panamintinus	Least Concern	54548	65.99	104.01	113.92	93.14	104.98
Tamias quadrimaculatus	Least Concern	38186	59.33	101.21	103.26	88.71	111.67
Tamias quadrivittatus	Least Concern	437728	50.19	110.51	111.82	104.08	115.64
Tamias rufus	Least Concern	210683	50.07	111.05	115.57	103.26	114.33
Tamias senex	Least Concern	152691	60.43	98.33	99.07	86.15	109.77
Tamias siskiyou	Least Concern	35536	68.56	93.24	96.09	84.38	99.25
Tamias sonomae	Least Concern	69432	53.98	91.20	94.92	83.05	95.64

Mammals

Species	Red List status	Range size	Climate breadth	AIE	IE CGCM3	IE CSIRO	IE BCCR
Tamias speciosus	Least Concern	100005	77.74	101.11	104.02	89.74	109.56
Tamias townsendii	Least Concern	252784	65.12	98.36	108.84	89.43	96.80
Tamias umbrinus	Least Concern	451361	54.68	108.05	111.75	98.18	114.23
Tamiasciurus douglasii	Least Concern	826950	89.13	97.42	104.68	88.47	99.10
Thomomys bulbivorus	Least Concern	10113	8.17	94.93	100.14	87.28	97.37
Thomomys clusius	Least Concern	11552	9.39	106.77	105.40	102.07	112.83
Thomomys idahoensis	Least Concern	172650	46.75	100.82	97.74	100.28	104.44
Thomomys mazama	Least Concern	126671	58.83	94.55	97.74	85.20	100.70
Thomomys monticola	Least Concern	79687	56.06	100.00	100.54	87.59	111.86
Thomomys townsendii	Least Concern	176744	23.94	109.15	111.88	96.88	118.70
Vulpes macrotis	Least Concern	2352248	93.46	110.79	113.95	103.94	114.46
Vulpes velox	Least Concern	958765	43.15	104.70	98.38	99.46	116.27
Zapus trinotatus	Least Concern	267669	68.88	97.44	107.58	88.82	95.93

Trees and shrubs

Species	Red List status	Range size	Climate breadth	AIE	IE CGCM3	IE CSIRO	IE BCCR
Abies amabilis	Least Concern	340589	98.39	98.48	117.87	92.00	85.57
Abies bracteata	Near Threatened	303	35.59	86.82	98.12	83.22	79.12
Abies concolor	Least Concern	265158	61.43	107.86	109.03	100.25	114.44
Abies magnifica	Least Concern	47459	50.75	98.44	99.58	86.79	108.87
Abies procera	Least Concern	55836	61.75	98.03	108.03	86.87	99.19
Acer circinatum	Not Evaluated	385216	68.70	97.29	106.60	88.99	96.30
Acer glabrum	Not Evaluated	2081766	66.09	97.69	102.55	95.46	95.02
Aesculus californica	Not Evaluated	98417	36.91	93.24	97.66	85.24	96.82
Agave utahensis	Not Evaluated	38398	38.20	111.40	122.50	101.78	109.91
Alnus oblongifolia	Not Evaluated	42925	38.43	115.46	117.28	113.00	116.09
Alnus rhombifolia	Not Evaluated	214181	65.16	96.27	100.36	87.56	100.91
Arctostaphylos pringlei	Not Evaluated	8896	32.29	111.84	119.45	107.43	108.66
Betula occidentalis	Not Evaluated	1276118	31.07	100.28	99.41	101.09	100.35
Canotia holacantha	Not Evaluated	59465	45.61	115.26	123.31	110.43	112.05
Castanopsis chrysophylla	Not Evaluated	129729	50.60	92.92	97.06	85.48	96.23
Ceanothus spinosus	Not Evaluated	6644	31.28	99.27	111.28	98.99	87.54
Ceanothus thyrsiflorus	Not Evaluated	45429	47.38	87.92	92.74	82.98	88.02
Cercocarpus betuloides	Not Evaluated	119611	59.70	114.04	130.58	113.44	98.12
Cercocarpus breviflorus	Not Evaluated	69504	47.39	98.68	103.37	89.94	102.73
Cercocarpus ledifolius	Not Evaluated	327548	39.05	92.84	97.71	86.63	94.19
Cercidium microphyllum	Not Evaluated	314336	31.34	115.75	114.84	114.62	117.79
Cercis occidentalis	Not Evaluated	79948	53.40	104.31	105.24	94.82	112.86
Cereus giganteus	Least Concern	239744	33.89	116.97	130.74	115.75	104.42
Chamaecyparis lawsoniana	Near Threatened	22258	40.89	91.16	96.80	85.62	91.07
Cornus glabrata	Not Evaluated	59822	58.68	90.81	94.11	83.47	94.86
Cornus nuttallii	Not Evaluated	418950	68.42	97.14	106.51	89.65	95.26
Cornus occidentalis	Not Evaluated	247147	54.83	93.43	99.04	86.32	94.92
Cornus sessilis	Not Evaluated	36853	44.02	97.68	100.35	87.57	105.12
Crataegus columbiana	Not Evaluated	79697	48.58	96.61	99.85	95.18	94.79
Crataegus douglasii	Not Evaluated	1591452	71.62	96.43	93.66	94.84	91.79
Crataegus erythropoda	Not Evaluated	26630	40.69	108.44	110.85	100.65	113.81
Crataegus saligna	Not Evaluated	8130	37.44	108.37	112.31	100.54	112.26
Cupressus bakeri	Vulnerable	1573	44.98	95.65	97.35	84.83	104.78
Cupressus goveniana	Endangered	964	26.33	84.11	89.74	78.30	84.28
Cupressus guadalupensis	Endangered	1521	17.11	100.24	113.42	101.62	85.69
Cupressus macnabiana	Least Concern	3094	30.20	93.03	96.54	83.90	98.65
Cupressus macrocarpa	Vulnerable	345	11.17	79.13	87.36	74.92	75.09
Cupressus sargentii	Vulnerable	4899	25.21	90.89	95.60	82.48	94.58

Trees and shrubs

Species	Red List status	Range size	Climate breadth	AIE	IE CGCM3	IE CSIRO	IE BCCR
Dalea spinosa	Not Evaluated	148714	20.39	111.60	136.71	107.58	90.51
Euonymus occidentalis	Not Evaluated	92848	37.00	92.47	97.84	86.29	93.28
Fraxinus cuspidata	Not Evaluated	15908	62.36	110.97	106.86	110.46	115.59
Fraxinus dipetala	Not Evaluated	86983	29.76	95.21	101.59	91.23	92.83
Fraxinus gooddingii	Not Evaluated	3290	29.28	124.62	133.19	126.42	114.24
Fraxinus latifolia	Not Evaluated	242511	56.17	94.78	100.63	87.20	96.52
Fraxinus papillosa	Not Evaluated	2890	37.79	118.91	124.04	118.11	114.59
Fraxinus velutina	Not Evaluated	130584	45.34	116.08	119.50	113.23	115.51
Fremontodendron californicum	Not Evaluated	50970	28.99	99.37	104.05	91.76	102.32
Fremontodendron mexicanum	Not Evaluated	1430	14.92	100.50	114.99	101.19	85.33
Garrya elliptica	Not Evaluated	51996	58.37	88.24	93.87	83.51	87.35
Holacantha emoryi	Not Evaluated	122614	21.88	114.69	132.98	109.93	101.16
Juglans californica	Vulnerable	7669	16.39	88.90	96.57	93.08	77.04
Juglans hindsii	Not Evaluated	2273	17.40	92.09	97.21	83.11	95.95
Juniperus californica	Least Concern	44651	37.79	94.34	103.49	92.13	87.38
Juniperus erythrocarpa	Not Evaluated	41770	43.38	117.00	121.24	114.49	115.27
Juniperus occidentalis	Least Concern	171453	29.49	103.17	105.63	89.07	114.81
Juniperus scopulorum	Least Concern	942596	55.66	99.00	101.01	96.83	99.12
Libocedrus decurrens	Not Evaluated	169872	58.86	97.19	100.16	87.12	104.27
Lithocarpus densiflorus	Not Evaluated	44692	45.47	90.95	95.71	85.50	91.63
Myrica californica	Not Evaluated	70410	70.46	89.17	94.10	84.22	89.20
Nolina bigelovii	Not Evaluated	37411	62.84	110.82	125.28	106.68	100.51
Opuntia fulgida	Least Concern	199042	38.05	117.05	129.65	118.76	102.76
Ostrya chisosensis	Not Evaluated	341	13.02	104.79	100.03	101.85	112.51
Ostrya knowltonii	Not Evaluated	6766	45.32	112.22	115.91	105.55	115.19
Photinia arbutifolia	Not Evaluated	132278	44.11	93.73	101.14	91.42	88.62
Picea breweriana	Vulnerable	2572	62.46	91.80	96.92	84.72	93.75
Picea engelmannii	Least Concern	1274194	46.79	95.53	99.26	95.21	92.12
Picea pungens	Least Concern	121546	45.45	108.75	110.35	101.63	114.27
Pinus albicaulis	Endangered	710598	51.82	92.62	99.76	93.55	84.56
Pinus aristata	Least Concern	29681	47.31	109.05	112.57	99.00	115.59
Pinus attenuata	Least Concern	26058	72.12	92.42	97.76	85.59	93.89
Pinus balfouriana	Near Threatened	3861	82.80	95.02	98.54	85.32	101.20
Pinus coulteri	Near Threatened	9504	32.23	93.61	102.44	92.54	85.84
Pinus flexilis	Least Concern	376066	45.35	100.95	101.18	97.64	104.03
Pinus lambertiana	Least Concern	167489	58.79	96.88	99.26	86.55	104.83
Pinus longaeva	Least Concern	12724	42.83	111.36	117.89	98.91	117.27
Pinus monophylla	Least Concern	112538	31.78	108.99	115.95	96.65	114.38
Pinus muricata	Vulnerable	3323	52.63	82.23	87.59	78.28	80.83
Pinus quadrifolia	Least Concern	7140	23.86	109.25	124.96	104.92	97.87
Pinus sabiniana	Least Concern	58176	38.31	95.69	100.03	88.10	98.94
Pinus washoensis	Not Evaluated	665	29.23	103.09	103.68	89.07	116.52
Platanus racemosa	Not Evaluated	95084	31.09	94.20	102.80	94.33	85.46
Platanus wrightii	Not Evaluated	144633	31.20	119.29	124.60	117.51	115.76
Populus arizonica	Not Evaluated	64708	33.61	111.69	108.88	110.32	115.88
Populus hinckleyana	Not Evaluated	328	12.73	108.60	98.97	111.16	115.68
Prosopis pubescens	Not Evaluated	210145	57.51	110.61	126.73	102.35	102.75
Prunus emarginata	Not Evaluated	823834	77.80	97.98	103.93	91.83	98.33
Prunus fremontii	Not Evaluated	34816	41.17	108.50	125.09	105.17	95.23
Prunus ilicifolia	Not Evaluated	81462	35.21	94.74	105.59	95.86	82.77
Prunus subcordata	Not Evaluated	156077	54.02	95.39	98.38	86.28	101.50
Pseudotsuga macrocarpa	Near Threatened	9495	40.24	96.77	104.21	96.43	89.68
Ptelea crenulata	Not Evaluated	35455	24.54	96.94	99.73	87.87	103.24
Quercus agrifolia	Not Evaluated	81678	30.40	88.83	98.01	88.71	79.89
Quercus ajoensis	Not Evaluated	2753	10.29	110.10	130.93	107.15	92.21

Trees and shrubs

Species	Red List status	Range size	Climate breadth	AIE	IE CGCM3	IE CSIRO	IE BCCR
Quercus chrysolepis	Not Evaluated	180579	58.98	94.88	99.07	87.01	98.57
Quercus douglasii	Not Evaluated	83874	29.30	95.24	99.81	88.32	97.57
Quercus dunnii	Not Evaluated	30843	28.79	114.76	122.56	109.45	112.28
Quercus emoryi	Not Evaluated	52949	32.30	118.29	123.41	115.81	115.67
Quercus engelmannii	Vulnerable	7980	16.31	97.79	110.65	98.67	84.05
Quercus gambelii	Not Evaluated	470259	46.92	111.36	113.74	104.37	115.96
Quercus garryana	Not Evaluated	205078	43.49	95.85	101.84	87.44	98.27
Quercus graciliformis	Critically Endangered	604	14.53	102.10	96.23	98.99	111.07
Quercus gravesii	Least Concern	7740	40.97	106.68	97.78	105.99	116.26
Quercus grisea	Not Evaluated	38246	41.96	114.34	112.38	113.23	117.42
Quercus hypoleucoides	Not Evaluated	42987	29.41	118.52	123.49	119.05	113.03
Quercus kelloggii	Not Evaluated	126415	54.93	95.27	98.23	86.01	101.56
Quercus lobata	Not Evaluated	138807	30.38	94.37	99.66	86.78	96.83
Quercus oblongifolia	Not Evaluated	28917	26.59	122.37	129.45	122.19	115.47
Quercus toumeyi	Least Concern	7412	29.31	120.63	126.46	119.78	115.63
Quercus turbinella	Not Evaluated	110586	40.05	114.96	121.72	110.27	112.90
Quercus wislizeni	Not Evaluated	115744	43.02	95.17	99.91	88.31	97.28
Rhamnus californica	Not Evaluated	285032	51.56	95.03	100.65	89.74	94.71
Rhamnus crocea	Not Evaluated	177860	37.51	99.97	107.86	95.20	96.86
Rhamnus purshiana	Not Evaluated	568088	83.58	97.95	105.65	92.74	95.40
Rhododendron macrophyllum	Not Evaluated	108823	48.45	93.70	99.74	86.38	94.97
Rhus choriophylla	Not Evaluated	18679	26.35	121.89	128.46	121.31	115.88
Rhus kearneyi	Not Evaluated	5885	32.54	106.22	124.17	108.04	86.45
Rhus laurina	Not Evaluated	37053	38.17	104.30	123.15	103.36	86.37
Rhus ovata	Not Evaluated	63568	35.48	108.57	122.61	105.96	97.14
Robinia neomexicana	Least Concern	68897	41.51	115.04	115.35	112.85	116.91
Salix fluviatilis	Not Evaluated	11457	20.00	96.47	103.18	87.99	98.26
Salix geyeriana	Not Evaluated	505112	51.55	101.11	100.70	98.31	104.31
Salix hindsiana	Not Evaluated	214672	39.04	92.18	97.30	84.42	94.81
Salix laevigata	Not Evaluated	179263	40.14	92.56	98.47	88.40	90.82
Salix lasiolepis	Not Evaluated	369468	70.42	94.36	99.36	87.18	96.54
Salix sessilifolia	Not Evaluated	30288	23.41	95.85	101.84	87.96	97.74
Salix tracyi	Not Evaluated	15739	29.19	87.46	91.14	83.51	87.73
Sambucus glauca	Not Evaluated	800540	76.83	99.59	104.76	94.90	99.11
Sambucus melanocarpa	Not Evaluated	320756	48.51	99.65	101.60	97.58	99.77
Sambucus velutina	Not Evaluated	18207	63.25	100.99	102.90	88.47	111.60
Sequoiadendron giganteum	Endangered	207	38.93	86.68	91.68	81.09	87.28
Sequoia sempervirens	Endangered	17802	44.08	98.52	100.90	89.82	104.84
Staphylea bolanderi	Not Evaluated	15222	53.52	102.27	106.53	93.41	106.86
Taxus brevifolia	Near Threatened	659801	98.80	97.87	107.87	91.38	94.35
Torreya californica	Vulnerable	4660	32.04	91.40	95.90	83.37	94.94
Umbellularia californica	Not Evaluated	123974	56.48	91.52	96.37	85.34	92.85
Vauquelinia californica	Not Evaluated	13845	36.62	117.81	125.94	116.12	111.36
Vauquelinia pauciflora	Not Evaluated	279	13.34	118.07	123.51	115.85	114.85
Washingtonia filifera	Least Concern	1704	75.51	106.61	124.69	102.11	93.04
Yucca brevifolia	Not Evaluated	86337	34.21	109.05	123.60	98.24	105.36
Yucca elata	Not Evaluated	349615	28.65	114.63	112.35	115.35	116.20
Yucca faxoniana	Not Evaluated	8338	11.07	110.12	101.56	113.41	115.39
Yucca mohavensis	Not Evaluated	95242	46.46	106.45	124.22	97.98	97.19
Yucca rostrata	Not Evaluated	6501	17.20	96.14	90.11	87.49	110.82
Yucca schottii	Not Evaluated	13945	26.41	121.13	127.51	120.37	115.52
Yucca torreyi	Not Evaluated	272518	29.39	109.12	103.48	108.87	115.01

Appendix III

CLIMATE DATASETS

The table below specifies which subsets of bioclimate variables were used for testing sensitivity of climate breadth and IE.

Number of variables	Variables used	Scenario
2	MAT MAP	Most basic model
8	MAT TD MAP MSP NFFD FFP Eref CMD	Some annual variables
16	TAV$_{wt}$ TAV$_{sp}$ TAV$_{sm}$ TAV$_{at}$ TMAX$_{wt}$ TMAX$_{sp}$ TMAX$_{sm}$ TMAX$_{at}$ TMIN$_{wt}$ TMIN$_{sp}$ TMIN$_{sm}$ TMIN$_{at}$ PPT$_{wt}$ PPT$_{sp}$ PPT$_{sm}$ PPT$_{at}$	All seasonal variables
20	MAT MWMT MCMT TD MAP MSP AHM SHM DD<0 DD>5 DD<18 DD>18 NFFD FFP bFFP eFFP PAS EMT Eref CMD	All annual variables
23	MAT MWMT MCMT TD MAP AHM SHM TAV$_{wt}$ TAV$_{sp}$ TAV$_{sm}$ TAV$_{at}$ TMAX$_{wt}$ TMAX$_{sp}$ TMAX$_{sm}$ TMAX$_{at}$ TMIN$_{wt}$ TMIN$_{sp}$ TMIN$_{sm}$ TMIN$_{at}$ PPT$_{wt}$ PPT$_{sp}$ PPT$_{sm}$ PPT$_{at}$	Some annual variables, all seasonal variables
32	MAT MWMT MCMT TD MAP MSP AHM SHM DD<0 DD>5 DD<18 DD>18 PAS EMT Eref CMD TAV$_{wt}$ TAV$_{sp}$ TAV$_{sm}$ TAV$_{at}$ TMAX$_{wt}$ TMAX$_{sp}$ TMAX$_{sm}$ TMAX$_{at}$ TMIN$_{wt}$ TMIN$_{sp}$ TMIN$_{sm}$ TMIN$_{at}$ PPT$_{wt}$ PPT$_{sp}$ PPT$_{sm}$ PPT$_{at}$	All annual variables, all seasonal variables, no frost-related variables

Number of variables	Variables used				Scenario
36	MAT	MWMT	MCMT	TD	All annual variables, all seasonal variables
	MAP	MSP	AHM	SHM	
	DD<0	DD>5	DD<18	DD>18	
	NFFD	FFP	bFFP	eFFP	
	PAS	EMT	Eref	CMD	
	TAV_{wt}	TAV_{sp}	TAV_{sm}	TAV_{at}	
	$TMAX_{wt}$	$TMAX_{sp}$	$TMAX_{sm}$	$TMAX_{at}$	
	$TMIN_{wt}$	$TMIN_{sp}$	$TMIN_{sm}$	$TMIN_{at}$	
	PPT_{wt}	PPT_{sp}	PPT_{sm}	PPT_{at}	
40	MAT	MWMT	MCMT	TD	All variables
	MAP	MSP	AHM	SHM	
	DD<0	DD>5	DD<18	DD>18	
	NFFD	FFP	bFFP	eFFP	
	PAS	EMT	Eref	CMD	
	TAV_{wt}	TAV_{sp}	TAV_{sm}	TAV_{at}	
	$TMAX_{wt}$	$TMAX_{sp}$	$TMAX_{sm}$	$TMAX_{at}$	
	$TMIN_{wt}$	$TMIN_{sp}$	$TMIN_{sm}$	$TMIN_{at}$	
	PPT_{wt}	PPT_{sp}	PPT_{sm}	PPT_{at}	
	$TMAX_{07}$	$TMIN_{01}$	PPT_{04}	PPT_{12}	