1 Administrative

Principal Investigator

Lucas Fortini, Pacific Island Ecosystems Research Center, U.S. Geological Survey. lfortini@usgs.gov

Cooperators / Partners

Kevin Brinck, Hawaii Cooperative Studies Unit, University of Hawaii at Hilo. brinck@hawaii.edu
James Jacobi, Pacific Island Ecosystems Research Center, U.S. Geological Survey. jjacobi@usgs.gov
Jonathan Price, Department of Geography and Environmental Sciences, University of Hawaii at Hilo. jpprice@hawaii.edu
Sam Gon, Senior Scientist / Cultural Advisor, The Nature Conservancy of Hawaii. sgon@tnc.org
Ann Sakai, Department of Ecology and Evolutionary Biology, University of California-Irvine. aksakai@uci.edu

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2 Public summary

The Hawaiian Islands are home to a variety of native species that have been subject to numerous threats including development of habitat for human use, predation by introduced herbivores, and competition with invasive plant species. In addition to these threats global climate change is expected to increase temperature and alter patterns of precipitation in Hawaii. This project models the relative vulnerability of native plant species to the effects of climate change, in order to assist resource managers in effectively allocating limited resources to efficiently preserve and protect current and future habitat for native plants.

We modeled vulnerability by creating an expert system – a network model linking biological traits of various plant species with the projected changes in species ranges under the effect of climate change. A panel of experts in Hawaiian plant species participated in the model design, identifying factors expected to affect a species' ability to successfully respond to climate change. Once the model results were available, this same panel verified that the model results agreed with their own expert opinion on a sample of species with which they were familiar.

The results are relative vulnerability scores for 1,056 native Hawaiian plant species. Due to limitations of the modeling process and the available data, the exact vulnerability scores are less important than the general ranking, and can be used to identify categories of species with high, middle, and low vulnerability to climate change.

3 Technical summary

We calculated the relative vulnerability of 1,056 native Hawaiian plant species under varying scenarios of climate change. Our methods improved upon the previous vulnerability assessment (Fortini et al. 2013) by incorporating life-history traits of the various plant species and modeling how they affect the species' ability to cope with climate change. Four different responses were modeled: 1) Tolerating the change in conditions, 2) Migrating to new suitable habitat, 3) Persisting in micro-refugia within existing habitat, or 4) Evolving to adapt to the new climate conditions. Life-history and geographic variables were combined in a categorical network model which defined the strength and direction of relationships between variables and how they affect the ways a species might respond to climate change.

Geographic variables were projected using three different climate scenarios and downscaling methods. The first was an updated version of the Zhang et al. (2012) dynamically downscaled climate model based on the A1B emission scenario. The other two were statistically downscaled models produced by Timm et al. (2014) based on RCP 4.5 and 8.5 radiative forcing scenarios. All three models are ostensibly applicable to end-of-21st Century climate, depending upon global fossil fuel use over the next decades. Life-history variables were collected from existing databases, compiled from published sources, and gathered by surveying Hawaiian botanical experts.

The modeled vulnerability scores were ranked, and we examined differences from the original vulnerability assessment, and differences resulting from the choice of climate downscaling model. The result is an updated list of relative vulnerability for native Hawaiian plant species. In addition, recent attention (e.g. Snover et al. 2013) has addressed how choice of downscaling model affects the results of ecological modeling. In this project, we have provided the first example in a Hawaiian system of how the choice of downscaling model affects ecological conclusions.

4 Purpose and objectives

The flora of the Hawaiian Islands is unique on a global scale for its high levels of endemism and represents the adaptive radiation of a small number of colonizing species over the past 30 million years (Price and Clague 2002). The combined impact of recent human-mediated invasive competitors, predators, and disease along with large-scale land-use change on isolated Hawaiian ecosystems is a well-recognized state of biodiversity crisis (Wagner et al. 1999, Sakai et al. 2002). In addition to these historical factors affecting the viability of native plant species, resource managers must also consider how global climate change will affect the native Hawaiian biota.

Global climate change is unequivocally linked to human activities (IPCC 2014) and is expected to affect numerous conditions that affect whether or not a given location is suitable habitat for a particular plant species. In Hawaii these factors are expected to include increased temperatures, changing atmospheric circulation, and precipitation patterns which may result in either an increase or decrease in precipitation depending upon orographic features of the landscape.

The goal of this project is to identify native plant species most vulnerable to the projected effects of climate change. By identifying which species are most (and least) vulnerable, we hope to provide a tool for resource managers to assist them in making efficient use of limited resources.

5 Organization and approach

This vulnerability assessment is calculated based on a categorical network model. Such models identify the relationships between variables – which properties of biology or geographic distribution affect which other properties, with “parent” variables affecting “child” variables (the network). Each variable is restricted to a small number of possible values (the categories). For example, a biological variable might describe a plant species as “short” or “tall” affecting its ability to distribute propagules. A geographic variable might describe the overlap between current and projected habitat ranges as “small” or “large” affecting its ability to tolerate climate changes in place. For each species, the model was populated with known geographic and life-history variables. The outputs were the posterior probabilities of a “Favorable” vs. “Unfavorable” response to climate change in the four modalities: tolerate, migrate, persist in micro-refugia, or evolve.

5.1 Network model

The categorical network model was based on the original Fortini et al. (2013) model, which used only geographic variables. To this model, we added life-history variables and their relationships to a species’ ability to cope with climate change by the way it affected its ability to continue its life cycle (survival, reproduction, propagation) or reflecting upon its current population status (population number and size or recognized concern status) or its ability to adapt to potential climate change (plasticity and genetic diversity). This network model was then presented to a panel of botanical experts familiar with the Hawaiian plant community. Variables, their relationships, and relative importance were evaluated and the model adapted to reflect the consensus of expert opinion. New life-history variables were added as the experts identified them, others had their definitions clarified or changed, and yet others were dropped from the model as unlikely to have a biological effect. This process was repeated in an iterative cycle until the configuration of variables and relationships stabilized. In addition, we performed a sensitivity analysis to identify variables with an unusually strong or weak effect on the model results, as variables with negligible effect on the results could be safely removed from the model.

5.2 Species range shifts

Using the Price et al. (2012) parameters, we modeled species ranges as a function of elevation, temperature, and precipitation as described in Jacobi et al. (2016). Our methods departed slightly from their procedure in that we did not exclude non-pioneer-classified species from young lava flows, and we projected species ranges for three different climate downscaling models. This method also differs from the climate projection used in the original Fortini et al. (2013) vulnerability assessment in that it explicitly models current elevation ranges as temperature boundaries under a single downscaling model. This method also accommodates coastal species by assuming no maximum temperature boundaries for species currently found at less than 100 m elevation, removing an artifact of the first assessment where coastal species were projected to have minimal or no future habitat due to increased temperatures.

5.3 Geographic variables

We projected future species ranges under three climate downscaling models: the dynamically downscaled model of Zhang et al. (2012) based on the A1B emission scenario and two statistically downscaled models by Timm et al. (2014) based on the RCP 4.5 and 8.5 radiative forcing scenarios. We then compared these projected ranges with a similar range based on contemporary temperature and rainfall data from the Giambelluca et al. (2013) rainfall atlas of Hawaii. For each set of comparisons, we calculated a range of variables characterizing the geographical differences between current and projected future species ranges. Some examples are: the amount of overlap between current and future range, the distance between disjoint current and future range, the degree of fragmentation in current and future range, and topological variation within future vs. current range.

Continuous geographic variables were transformed into discreet categories by defining equally sized groups using quantiles of the population of all species. For example, a geographic variable with levels of “Far” vs. “Near” would use the median as the cutpoint, so half of the 1056 species would receive a value of “Far” and half “Near”. Similarly, variables with five discreet categories ranging from “Very Small” to “Very Large” would divide the population of species into fifths using the 20, 40, 60, and 80th percentiles of the population range.

5.4 Life-history variables

Life history information for our 1056 species were collected from multiple sources. Wagner et al. (1999) and Price et al. (2012) represent two major published collections. We also solicited data from other organizations and individuals working with Hawaiian plants. Finally, we selected a set of eleven life-history variables with a significant effect on model outputs and sent surveys to Hawaii botanical experts. Individual experts received from 300-350 species, specific to their island of expertise where they preferred. Experts were encouraged to give their best answer based on their expertise, even if only an educated guess, but were otherwise told to leave a species or question blank.

Our panel of expert botanists reviewed each life-history variable to define their meaning. These definitions often determined the category for a given species, e.g., a plant species is either a fern or it is not a fern, it is tolerant of inundation or it is not. Continuous measurements were usually treated similarly to geographic variables, for example the range in leaf size was “Small” or “Large” split at the median of values for which information was available. There were some exceptions made on a biological basis, for example the number of populations used the 90% percentile as a cut-off between “Small” and “Large” because relatively few native species have more than a handful of populations. Other breakpoints were chosen to separate an obviously bi-modal distribution. Finally, one inherently subjective variable was categorized according to a reproducible algorithm. Distinct flower color was assigned by assembling a list of adjectives used to describe flower color, assigning “Strong”, “Medium”, or “Weak” to all the colors on that list, and assigning “Distinct” to species that had only strong colors, a strong plus a medium or weak color, or three or more medium colors used in the descriptions.

5.5 Model parameterization

There are two ways in which a categorical network model can be tuned. The first is the probability of a variable having a particular value for species where that variable is not available, e.g. a variable that could be either “Short” or “Tall” might have even odds of either value, or “Short” could be ten times more likely than “Tall”. This can be seen as analogous to the Bayesian prior in a traditional statistical model. The second is the relative weights the one or more parent variables have on determining the value of child variables in the network. These weights can be considered analogous to regression coefficients in a traditional linear model.

For the most part, unknown variables were assumed to have equal probability across their possible categories. We made an adjustment after our original runs revealed a possible bias in life-history variables where information was available for only a few species. It is likely that species where most life-history information is known are also most common and inherently less vulnerable than rarer, less-known species. For this reason we adjusted the prior probability to make the less-favorable value more likely (usually from even odds to 2 to 1 against the favorable value, based on sensitivity analysis and an apparent correlation in earlier models) under the assumption that less-known species are usually less prevalent and therefore already more vulnerable to climate change. Finally, some variables in the model have specific biological effects that make them behave like "switches" in the network. For example, the variable "Fern" explicitly interacts with other parent variables to remove the effect of pollinator availability on a species' ability to reproduce.

5.6 Model implementation

The network model has four output nodes that are the ultimate children of all the other variables in the model. Each of these nodes represents the probability that a species has a Favorable vs. Unfavorable ability to respond to climate change via: 1) Tolerating the change in place, 2) Migrating to a new range, 3) persisting in Micro-refugia, or 4) Evolving to meet new climate conditions. Each of these posterior probabilities is determined by the value of the other variables and the relationships defined by the network model.

Missing values introduce uncertainty in the model outputs. For variables with missing information, we simulate the uncertainty by calculating the outputs for all possible values of the missing data. In practice, with more than a few missing variables it is computationally infeasible to estimate all possible combinations. Instead we generate a large number (1,000) of values for each missing variable by sampling from its prior distribution (e.g., sampling from "Tall" or "Short" from an even (1:1) prior with those two categories, or sampling from "Tall" or "Short" or "Short" if the prior is 1:2). An additional source of uncertainty arrives from our expert-solicited data; sometimes multiple experts would provide different responses for the same species. In such cases we treated the experts' opinions as the prior distribution and sampled from that.

From this set of 1,000 samples of the data, accounting for unknown and uncertain values, we randomly selected 100 combinations and calculated the posterior probability of a Favorable response for each of our four output variables. The mean and standard deviation was calculated for each output, and the mean taken as the point estimate of the probability of a Favorable outcome for each species in each of the four metrics. Finally, we calculated a vulnerability index for each species. If p_{Tol}, p_{Mig}, p_{MR}, and p_{Evo} are the probability of a favorable response to climate change via Toleration, Migration, persistence in Micro-refugia, or Evolution, then vulnerability (V) is given by:

$$V = \left(1 - \frac{p_{Mig} + p_{MR} + p_{Evo}}{3}\right) \times (1 - p_{Tol})$$

Note that Toleration is more heavily weighted than the other three responses. This reflects the reasoning that, for a species with a high likelihood of tolerating a given climate shift, other modalities are less important. Secondly, this index inverts the numerical interpretation of the raw metrics. The raw metrics are the probabilities of a Favorable response (higher scores imply less vulnerability to climate change) while higher values of the index indicate greater vulnerability to climate change.

6 Project results

6.1 Climate envelopes

In the course of this vulnerability assessment, we modeled species ranges for 1056 native Hawaiian plant species. In addition to modeled range under current climate conditions, we modeled conditions under three different climate downscaling models. The results allow for a comparison of how the choice of downscaling model affects the forecasts of ecological models. As an example, Figure 1 shows the distribution of changes in species range under the three climate models across all 1056 species. For this particular metric the A1B and RCP 4.5 models produce more similar distributions than the RCP 8.5 model, which shows a relative preponderance of decreases in percent change in range area compared to the other two. Other metrics (all model inputs are available as a data product for this project) show greater similarity between A1B and RCP 8.5 or essentially identical distributions for all three models. GIS shapefiles describing statewide range maps under all three climate scenarios are also available as data products of this project.

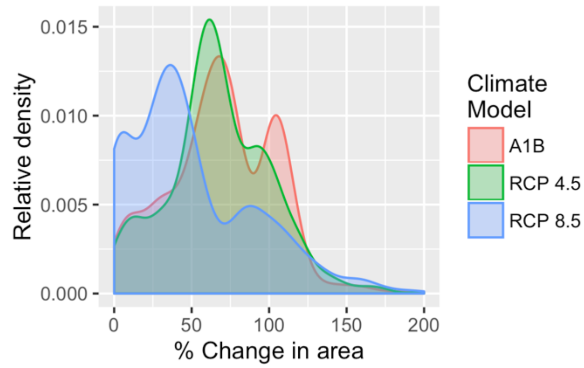

Figure 1. Distribution of percent change in the area of species range from present-day climate conditions to those projected by three different climate downscaling models.

6.2 Relative vulnerability

After running the model to produce measures of each species' ability to cope with climate change in each of the four modalities, and summarizing the four scores as a single vulnerability index, we were able to rank each species, and classify each as being of high, medium, or low relative vulnerability among native Hawaiian plant species. Raw scores and indexes are available as a separate data product, and summarized in a digital appendix to this report. Table 1 shows sample results, displaying percent-scaled ranks for the most, middle, and least vulnerable species as ranked by the vulnerability index calculated based on the dynamically downscaled A1B model. The table shows how the relative values of the four output metrics affect the index score. It also shows index scores calculated based on the two statistically downscaled climate models and the phase 1 downscaling assessment. Finally, it shows the change in vulnerability between the phase 1 assessment and the current project.

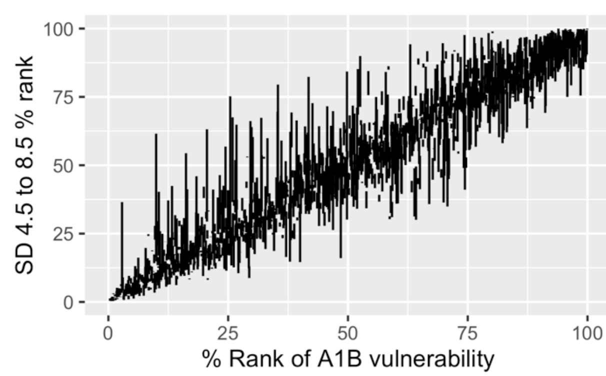

Figure 2. Correlation between % scaled vulnerability ranks by climate downscaling model. Horizontal axis is based on the dynamically downscaled A1B model, while vertical bars are the range in ranks between the statistically downscaled RCP 4.5 and 8.5 models.

Figure 2 demonstrates the correlation of relative vulnerability among the three downscaling models. The greatest differences are between the RCP 4.5 and 8.5 models, but both of those are roughly correlated with the A1B model, and the range of the two RCP models usually incorporates the A1B model, as shown by the linear trend. As a final check of the model results, we requested our panel of expert botanists to spot-check results by selecting candidate species with which they were especially familiar. They compared the models relative vulnerability assessment (high, medium, or low vulnerability) with their expert opinion. There was general convergence of model and expert opinion.

Table 1. Most, middle, and least vulnerable species according to the percentage-scaled vulnerability index calculated from the dynamically downscaled A1B model. Also shown are the scaled individual response metrics (Tolerate, Migrate, Micro-refugia, and Evolve). For comparison, we show the percent scaled vulnerabilities from the statistically downscaled RCP 4.5 and 8.5 models, as well as the vulnerability from the phase 1 assessment (based on an A1B model) and the change in percent-scaled vulnerability rank.

	Downscaled A1B climate model				Vulnerability index				
Species	Tol.	Mig.	M.R.	Evo.	A1B	RCP 4.5	RCP 8.5	Phase 1	Change
Entada phaseoloides	3.8	12.1	0.3	1.9	100.0	99.4	99.5	91.3	-8.7
Geranium hanaense	0.7	0.3	14.2	4.9	99.9	99.7	100.0	94.4	-5.5
Cyrtandra procera	0.1	5.7	19.6	29.5	99.8	90.5	99.4	72.9	-26.9
Sanicula kauaiensis	5.1	0.2	22.2	0.4	99.8	99.1	94.7	74.1	-25.6
Cyrtandra calpidicarpa	3.2	8.0	2.6	17.5	99.7	91.0	89.9	61.8	-37.9
Coprosma elliptica	5.0	0.5	18.5	1.6	99.6	96.1	87.7	92.7	-6.9
Cyrtandra rivularis	9.6	1.3	4.6	0.2	99.5	98.0	93.7	62.2	-37.3
Pritchardia schattaueri	6.6	1.8	6.2	1.5	99.4	89.8	95.5	88.6	-10.8
Cyrtandra ferripilosa	2.2	5.8	14.7	3.3	99.4	95.3	92.5	77.4	-21.9
Metrosideros macropus	14.5	0.1	1.7	0.2	99.3	99.9	95.1	64.4	-34.9
…		…				…			
Viola lanaiensis	33.2	67.4	47.9	75.3	53.3	55.4	58.2	92.3	39.0
Gahnia lanaiensis	42.4	51.3	62.9	36.8	53.2	50.5	59.3	90.5	37.3
Bidens mauiensis	47.4	40.2	32.8	68.5	53.1	53.8	57.4	63.2	10.0
Psychotria mariniana	32.1	62.8	44.9	84.6	53.0	44.0	43.5	32.2	-20.7
Euphorbia celastroides	55.2	47.0	36.8	35.5	52.9	64.9	54.6	25.7	-27.2
Melicope haupuensis	49.8	53.8	26.4	64.7	52.7	64.7	66.5	77.3	24.6
Cyanea longiflora	40.8	44.4	46.9	74.6	52.6	71.3	90.0	68.6	16.1
Pritchardia hillebrandii	40.7	61.0	40.2	68.7	52.4	53.5	47.9	88.7	36.3
Kanaloa kahoolawensis	49.6	37.9	72.5	22.6	52.1	52.0	44.8	99.9	47.7
Cyrtandra kohalae	58.5	46.9	56.6	16.6	52.1	68.5	85.2	58.7	6.6
…		…				…			
Santalum paniculatum	97.7	98.5	100.0	72.5	1.0	1.7	0.3	11.0	10.1
Carex wahuensis	98.0	99.4	98.0	96.0	0.7	1.2	0.6	8.5	7.7
Astelia menziesiana	98.7	98.5	96.8	97.6	0.6	1.0	1.5	9.8	9.1
Nototrichium sandwicense	99.8	95.2	98.8	80.3	0.6	0.3	1.1	29.6	29.0
Colubrina oppositifolia	99.5	97.6	99.6	89.6	0.5	0.2	0.2	32.6	32.1
Hesperocnide sandwicensis	97.1	99.9	99.4	99.8	0.4	0.9	0.5	24.9	24.5
Bidens menziesii	97.6	99.5	99.8	99.7	0.3	0.5	1.3	19.2	18.9
Capparis sandwichiana	99.9	98.9	89.1	91.2	0.2	0.6	0.6	43.8	43.6
Scaevola kilaueae	100.0	87.7	91.3	65.3	0.2	0.1	0.1	22.8	22.7
Adenophorus tamariscinus	99.8	99.6	99.2	98.7	0.1	0.2	0.2	1.6	1.5

7 Analysis and findings

There was a general pattern of agreement among the vulnerability assessments under the three different climate downscaling models. There was also agreement between the current assessment and the previous model. Where there was significant divergence it could sometimes be explained by improvements to the model made in this project. For example, in Table 1 the greatest change in vulnerability was for *Kanaloa kahoolawensis*. This is a coastal species, and the current model better assumes it will be able to accommodate increasing temperature, whereas under the previous model it had no potential range in the future. Another anomaly is *Viola lanaiensis*. This species was classified as highly vulnerable under the previous assessment, and in this project it had mid-range scores in most metrics, but a relatively high (75th percentile) rank in the Evolve response, which was introduced in the newer model.

It should be noted that the species range models used in this vulnerability assessment were relatively simple, using only temperature, rainfall, elevation, and broad geographic constraints to determine potential range. In practice, there are other geophysical parameters such as substrate type, and permeability, as well as climatic parameters such as insolation, temperature extremes, and evapotranspiration that could be expected to change along with the global climate. In addition, climate downscaling techniques are expected to improve, providing higher spatial resolution and better accommodation of the steep altitude gradients that drive climate effects on an individual species scale.

When interpreting these vulnerability results it is important to treat them as relatively broad categories rather than definitive rankings. Fundamentally, any model is a lower-precision representation of the real world, and there is uncertainty associated with the biological and climate-model-based geographic variables used as inputs. The vulnerability scores our model produces should be treated as approximate rather than absolute. Even if the model and inputs were perfect, there is incomplete data for most species, so our output metrics are based on a stochastic sample of a posterior distribution. It would not be proper to conclude from Table 1 that *Entada phaseoloides* (rank 1, most vulnerable) is more vulnerable than *Geranium hanaensei* (rank 2), but it is very likely that it is more vulnerable to the effects of climate change than *Adenophorus tamariscinus* (rank 1056).

8 Conclusions and recommendations

Climate is a key predictor of the suitable range of plant species. In the course of our modeling, we examined the effects of three different downscaling models on projecting the potential range of 1056 native Hawaiian plant species at the end of the 21st Century. The results show that there are differences in the projected ranges but for the most part, they are relatively minor. Where there are differences there is a tendency for the dynamically downscaled A1B to be more like the statistically downscaled RCP 8.5, but that pattern is not universal (see Figure 1). Thus, we can present these results as evidence that – when considering how climate change will affect the geographic ranges of native Hawaiian plant species – the choice of downscaling model does not have a major effect.

Our vulnerability model produces a relative score measuring the vulnerability of plant species to the effects of climate change on temperature and precipitation. The results are in broad agreement with the rankings of the previous (Fortini et al. 2013) assessment, and spot checks are in accordance with expert opinion. Major differences are often attributable to improvements in the species range modeling and the vulnerability model. Different climate downscaling models have minor effects on the exact vulnerability ranking of species, and do not affect broader (decile- or quartile-scale) rankings as we recommend the results be used.

9 Management implications and products

The relative vulnerability ranks produced by this project will assist resource managers in prioritizing species for conservation and mitigation in the face of climate change. We provide raw metric scores as well as vulnerability indexes and rankings. Although the full, digital table of results contains scores from all three climate downscaling models, as mentioned above, the choice of downscaling model does not affect interpretation of relative vulnerability.

We also produced species range maps for climate conditions projected to the end of the century. Resource managers interested in a particular species can download GIS shapefiles to see the projected ranges of native plant species under the three climate downscaling models. This information may inform decisions about land management or acquisition to preserve and protect habitat that will be suitable for species of concern into the future. While not as detailed in interpretation as the maps produced by Jacobi et al. (2016), our results encompass a wider range of species.

To populate the life-history traits of the categorical network model, we compiled a database of physical and life-history traits of native Hawaiian plant species. This database – which also includes the geophysical parameters used to fit the model – is available online, and may serve as a resource for scientists and resource managers working with native Hawaiian plant species.

Running our categorical network model involves a great deal of data processing. Species range maps are processed to extract geospatial variables, which are then categorized and combined with biological trait data. The network model is then run multiple times for each species to generate a simulated posterior distribution of the probability of a species favorably coping with climate change by four methods (Tolerate, Migrate, persist in Micro-refugia, and Evolve). We have developed a tool chain using the Python computer language in an ArcGIS framework and R statistical computing environment to carry out these steps and produce results similar to those in Table 1 and the digital appendix to this report. This set of of tools is now available. If new and improved climate downscaling models, or improved species range models become available, updating the vulnerability assessment is now a relatively straightforward process. The tools are also applicable to any other ecological system where projected changes in species ranges are available. Using an adaptation of our categorical network model, or a model designed specifically for the new system, our tool chain simplifies the process of applying our technique to other ecological communities.

10 Outreach

As this project is an expansion of the first Hawaiian plant vulnerability assessment released in 2013, it benefits from a wide community of plant conservation practitioners that have participated in it since 2011. Most importantly, our expert-elicitation exercise detailed in the report served two purposes. The first was to gather species information to feed our models, but the second allowed us to engage with a substantial portion of Hawaii's plant conservation community about our project goals and products. We contacted over 20 top plant experts to discuss our project's aims and goals and several volunteered a significant amount of their time to help.

Besides this significant elicitation effort, there are simply too many standard outreach actions for an exhaustive list. Two notable examples are the IUCN workshop on rare plant conservation organized by PEPP, where we discussed the upcoming release of the assessment to a large group of plant conservationists from Hawaii and elsewhere, and at the Annual OANRP meeting where we discussed the vulnerability of rare Hawaiian plants.

In several other events we have discussed the assessment goals and progress as well with other managers and researchers: the Hawaii Ecosystems Meeting held in July 2015; a landscape planning meeting for DOFAW in Maui; several PICCC steering committee meetings; at the 2015 regional meeting for the FWS Inventory and Monitoring program. With the work now concluded, we will continue to engage with partners (DOFAW, FWS, PEPP, TNC, NPS, Army) at key management organizations one-on-one to discuss our new products and determine if any additional synthesis efforts are necessary to address individual stakeholder needs. This was the process we adopted in the precursor assessment that clearly led to the widest consideration/ adoption of our results.

References

Fortini, L.B., Price, J., Jacobi, J., Vorsino, A., Burgett, J., Brink, K., Amidon, F., Miller, S., Gon, S., Koob, G., and Paxton, E., 2013, A landscape-based assessment of climate change vulnerability for all native Hawaiian plants: Hilo, University of Hawai`i, Hawai`i Cooperative Studies Unit Technical Report HCSU-044

Giambelluca, T.W., Chen, Q., Frazier, A.G., Price, J.P., Chen, Y.-L., Chu, P.-S., Eischeid, J.K., and Delparte, D.M., 2013, Online Rainfall Atlas of Hawai`i: Bulletin of the American Meteorological Society v. 94 p. 313–316. [Also available at http://dx.doi.org/10.1175/BAMS-D-11-00228.1.]

IPCC, Intergovernmental Panel on Climate Change, 2014, Climate Change 2014—Impacts, Adaptation, and Vulnerability, Part A—Global and Sectoral Aspects, Contribution of Working Group II to the Fifth Assessment Report of the Intergovernmental Panel on Climate Change, Field, C.B., Barros, V.R., Dokken, D.J., Mach, K.J., Mastrandrea, M.D., Bilir, T.E., Chatterjee, M., Ebi, K.L., Estrada, Y.O., Genova, R.C., Girma, B., Kissel, E.S., Levy, A.N., MacCracken, S., Mastrandrea, P.R., and White, L.L., eds.: Cambridge, Cambridge University Press.

Jacobi, J.J., Camp, R.J., Berkowitz, S.P., Brinck, K.W., Fortini, L.B., Price, J.P., and Loh, R.M. 2016. Assess the potential impacts of projected climate change on vegetation management strategies within Hawaii Volcanoes National Park. PICSC Final Report. URL: https://nccwsc.usgs.gov/

Price, J. P., and D. A. Clague. 2002. How old is the Hawaiian biota? Geology and phylogeny suggest recent divergence. Proceedings of the Royal Society of London Series B 269:2429–2435.

Price, J.P., Jacobi, J.D., Gon, S.M., III, Matsuwaki, D., Mehrhoff, L., Wagner, W., Lucas, M., and Rowe, B., 2012, Mapping plant species ranges in the Hawaiian Islands—Developing a methodology and associated GIS layers: U.S. Geological Survey Open-File Report 2012–1192, 34 p. [Also available at http://pubs.usgs.gov/of/2012/1192/.]

Sakai, A., W. Wagner, and L. Mehrhoff. 2002. Patterns of endangerment in the Hawaiian flora. Systematic Biology 51:276–302.

Snover, A.K., N.J. Mantua, J.S. Little, M.A. Alexander, M.M. McClure, and J. Nye. 2013. Choosing and using climate-change scenarios for ecological-impact assessments and conservation decisions. Conservation Biology 27:1147-1157.

Timm, O.E. T.W. Giambelluca, and H.F. Diaz. 2014. Statistical downscaling of rainfall changes in Hawaii based on the CMIP5 global model projections. Journal of Geophysical Research: Atmospheres. 2014: 92-112.

Wagner, W. L., D. R. Herbst, and S. H. Sohmer. 1999. Manual of the flowering plants of Hawai'i. University of Hawai'i Press, Bishop Museum Press, Honolulu, HI.

Zhang, C., Wang, Y., Lauer, A., and Hamilton, K., 2012, Configuration and evaluation of the WRF model for the study of Hawaiian Regional Climate: Monthly Weather Review v. 140 p. 3259–3277.