

Using climate projections to assess ecosystem vulnerability at scales relevant to managers

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Citation: Triepke, F. J., E. H. Muldavin, and M. M. Wahlberg. 2019. Using climate projections to assess ecosystem vulnerability at scales relevant to managers. *Ecosphere* 10(9):e02854. 10.1002/ecs2.2854

Abstract. Land managers require information about the ongoing and potential effects of future climate to coordinate responses for ecosystems, species, and human communities at scales that are operationally meaningful. Our study focused on the vulnerability for all upland ecosystem types of Arizona and New Mexico in the southwestern United States. Local vulnerability across the two-state area was represented by the level of departure for late 21st-century climate from the characteristic pre-1990 climate envelope of the ecosystem type at each given location, resulting in a probability surface of climate impacts for the two-state area and an uncertainty assessment based on agreement in results among multiple global climate models. Though the results varied from one ecosystem type to the next, the majority of lands were forecast as high vulnerability and low uncertainty, reflecting significant agreement among climate model projections for the southwestern United States. We then tested our results in relation to ongoing ecological processes that have both regional and global change implications and discovered significant relationships with wildfire severity, upward tree species recruitment, and the encroachment of scrub into semidesert grassland. The testing helped determine the efficacy of the vulnerability surface, as a product of relatively high spatial and thematic resolution, in supporting local planning and management decisions. Most important, this study links climate and changes in vegetation by ecosystem processes that are already ongoing. The results affirm the value of climate model downscaling and show that this portable approach to correlative modeling has value in determining the location and magnitude of potential climate-related impacts.

Key words: climate envelope; climate exposure; climate sensitivity; climate vulnerability; discriminant analysis; fire severity; global change; model validation; scrub encroachment.

Received 12 July 2019; **accepted** 15 July 2019. Corresponding Editor: Debra P. C. Peters.

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INTRODUCTION

Assessing ecosystem vulnerability at subregional scales is a critical need for resource specialists making on-the-ground management decisions. This is an important step in evaluating future impacts to ecosystems and, in turn, to associated biota, watersheds, and socioeconomic

resources (Friggens et al. 2013, Gutzler 2013, Hand et al. 2018). Evaluating vulnerability and uncertainty is part of an overall adaptation framework that also includes characterizing change and elucidating strategy and then responding to assessment results through management and monitoring (Halofsky et al. 2018). Accordingly, it is necessary to understand

vulnerability patterns at subregional scales that are relevant to land managers (e.g., watersheds to subbasins; Peterson et al. 2011, Buotte et al. 2016).

To address this need, we used the diverse landscapes of the southwestern United States to test a process of applying ecological knowledge and downscaled climate models to assess vulnerability at an operationally relevant scale. In the context of our study, vulnerability refers to the collective inferences of future climate (exposure) and its departure from pre-1990 (1961–1990) envelopes (sensitivity) of probable change to predominant vegetation features and not actual impacts (our assessment does not consider the element of adaptive capacity per USGCRP 2011). In the Southwest, several global climate model (GCM) projections indicate altered climate patterns and a continuing trend toward warmer and dryer conditions (Seager et al. 2007, Gutzler and Robbins 2010, Jones and Gutzler 2016). Climate-related effects to vegetation patterns will likely stem from an increase in summer temperatures, increase in frost-free days, reduced snow accumulation and incidence of albedo, and other related indicators (Thomey et al. 2011, Williams et al. 2013). The continuing alteration of landscapes coupled with clear indications of a changing climate has signaled an urgency among managers to determine probable future outcomes and options for climate adaptation (Friggens et al. 2013, Williams et al. 2013, Thorne et al. 2017). This is particularly the case in the Southwest where several major temperate ecosystem types find their southernmost limits in North America (Brown et al. 1998) and hence would be expected to be particularly sensitive to a warming climate (Boisvert-Marsh et al. 2014).

Over the past decade, scientists have forecasted and described changes from climate to natural systems of the Southwest, projected specific impacts, and articulated reasonable responses in the form of conservation planning (Enquist and Gori 2008, Cross et al. 2012, Notaro et al. 2012, Rehfeldt et al. 2012, Garfin et al. 2013, Treasure et al. 2014, Jennings and Harris 2017, Thorne et al. 2017). To date, assessments for vulnerability in the Southwest have focused on particular ecological components or geographical areas (e.g., Comer et al. 2012), or have relatively coarse

thematic or spatial outputs (>1:1,000,000 map scale) that are useful for broad policy and strategy but may be too general for subregional applications (Thorne et al. 2017). For these reasons, we chose an approach that would generate a regional assessment of increased spatial and thematic detail to convey vulnerability to future climate.

For thematic units, we opted for ecological response units (ERUs), a finer ecosystem type classification that encompasses vegetation concepts that are familiar to resource managers and biologists in the southwestern United States (Moreland et al. 2017, Triepke et al. 2017). The ERU framework represents all major ecosystem types (Table 1) including 26 ERUs and numerous subclasses. We suggest that ERUs are at a thematic resolution that is sufficiently general enough to buffer the uncertainty of climate forecasts and ecological modeling that finer biotic units such as plant associations and individual species do not, and that ERUs still have enough thematic detail to support project-level analysis, planning, and management. By this approach, greater predictive accuracy is assumed by the forfeiture of precision; that is, fewer and more general biotic units are accepted to improve product accuracy (Triepke 2017b). Using the ERU framework, our focus was on the probability of change in overall vegetation pattern, knowing that vegetation provides much of the basic structure and resources for ecological function and species habitat (Box and Fujiwara 2005).

We used a correlative modeling approach that involved a handful of select variables to minimize compounding error associated with interacting models, inputs, and parameterization, and that had spatial outputs that can be readily integrated with GIS analyses. With this approach, the departure of future climate at the year 2090 from pre-1990 climate was computed at the local scale to provide an inference of vulnerability. Model outputs were then summarized to subregional scales (Buotte et al. 2016), including National Forests (7220–11,990 km²), by reporting vulnerability projections for each ERU. Outputs from multiple global climate models were compared to determine the uncertainty of our predictions. For validation, we compared key ecological processes of the past decade—wildfire incidence, shrub encroachment in grasslands, and changes in tree species distribution—to our

Table 1. Climate vulnerability assessment results for the southwestern region, showing the percentages of vulnerability and uncertainty categories within each ecological response unit (ERU).

Vulnerability category	Area (%)	Uncertainty category		
		Low	Moderate	High+
All ERUs (588,237 km ²)				
Low	6	2	4	0
Moderate	24	1	16	7
High	22	4	17	0
Very High	48	43	5	0
Uncertainty total		50	42	8
Cold types				
Alpine and Tundra (44 km ²)				
Low	0	0	0	0
Moderate	0	0	0	0
High	0	0	0	0
Very High	100	100	0	0
Uncertainty total		100	0	0
Spruce-Fir Forest (3925 km ²)				
Low	10	0	9	0
Moderate	47	0	35	12
High	25	16	9	0
Very High	19	19	0	0
Uncertainty total		35	53	12
Bristlecone Pine (29 km ²)				
Low	0	0	0	0
Moderate	4	0	4	1
High	15	14	1	0
Very High	80	80	0	0
Uncertainty total		94	5	1
Mixed Conifer w/Aspen (3064 km ²)				
Low	20	2	17	0
Moderate	47	0	26	21
High	20	4	15	0
Very High	13	13	0	0
Uncertainty total		20	58	22
Mixed Conifer-Frequent Fire (11,240 km ²)				
Low	20	7	13	0
Moderate	43	1	26	16
High	22	4	18	0
Very High	14	14	0	0
Uncertainty total		26	58	16
Ponderosa Pine Forest (28,608 km ²)				
Low	5	2	4	0
Moderate	43	0	28	15
High	30	11	19	0
Very High	22	21	0	0
Uncertainty total		35	51	15

(Table 1. Continued.)

Vulnerability category	Area (%)	Uncertainty category		
		Low	Moderate	High+
Pinyon-Juniper Sagebrush (9173 km ²)				
Low	0	0	0	0
Moderate	12	0	7	5
High	12	6	7	0
Very High	76	75	0	0
Uncertainty total		81	14	5
Gambel Oak Shrubland (1367 km ²)				
Low	11	3	9	0
Moderate	34	0	23	11
High	19	6	13	0
Very High	36	35	1	0
Uncertainty total		43	46	11
Sagebrush Shrubland (15,198 km ²)				
Low	29	19	10	0
Moderate	51	8	36	6
High	16	0	15	1
Very High	5	2	3	0
Uncertainty total		29	64	7
Intermountain Salt Scrub (10,428 km ²)				
Low	4	2	2	0
Moderate	23	2	16	5
High	23	7	16	0
Very High	50	41	9	0
Uncertainty total		52	43	5
Sand Sheet Shrubland (11,323 km ²)				
Low	1	1	0	0
Moderate	38	3	23	11
High	33	9	24	0
Very High	28	25	3	0
Uncertainty total		38	51	11
Montane/Subalpine Grassland (2668 km ²)				
Low	36	17	19	0
Moderate	47	1	27	19
High	13	1	12	0
Very High	4	4	0	0
Uncertainty total		23	58	19
Colo. Plat./Great Basin Grass. (64,850 km ²)				
Low	2	1	2	0
Moderate	12	0	7	4
High	14	4	10	0
Very High	72	71	1	0
Uncertainty total		76	20	5

(Table 1. Continued.)

Vulnerability category	Area (%)	Uncertainty category		
		Low	Moderate	High+
Mild types				
Ponderosa				
Pine-Evergreen Oak (3935 km ²)				
Low	6	1	5	0
Moderate	47	0	26	20
High	32	5	27	0
Very High	15	14	1	0
Uncertainty total		20	59	21
Madrean Pinyon-Oak Wood. (4411 km ²)				
Low	12	2	9	1
Moderate	51	2	27	22
High	27	2	24	1
Very High	9	9	1	0
Uncertainty total		15	61	24
Madrean Encinal Woodland (5254 km ²)				
Low	4	0	4	0
Moderate	21	1	11	9
High	32	2	30	0
Very High	43	42	1	0
Uncertainty total		44	46	10
Pinyon-Juniper Evergreen Shrub (15,908 km ²)				
Low	28	7	21	0
Moderate	50	6	31	13
High	16	1	15	0
Very High	7	5	2	0
Uncertainty total		18	69	14
Interior Chaparral (9936 km ²)				
Low	25	6	18	1
Moderate	56	3	34	19
High	17	1	15	1
Very High	2	0	2	0
Uncertainty total		9	69	22
Semidesert grassland (94,912 km ²)				
Low	4	0	3	1
Moderate	13	0	9	4
High	32	4	26	1
Very High	51	47	5	0
Uncertainty total		52	42	6
Neutral types				
Pinyon-Juniper Woodland (22,199 km ²)				
Low	8	3	5	0
Moderate	42	2	27	13
High	32	5	27	0
Very High	18	13	5	0
Uncertainty total		23	64	13

(Table 1. Continued.)

Vulnerability category	Area (%)	Uncertainty category		
		Low	Moderate	High+
Pinyon-Juniper Grass (24,607 km ²)				
Low	7	1	6	0
Moderate	30	1	18	11
High	32	8	24	0
Very High	32	30	2	0
Uncertainty total		39	49	12
Juniper Grass (37,488 km ²)				
Low	3	1	2	0
Moderate	43	1	30	12
High	36	4	32	0
Very High	19	16	3	0
Uncertainty total		22	66	12
Mtn. Mahogany Mixed Shrub. (2504 km ²)				
Low	14	3	10	1
Moderate	35	0	20	15
High	29	3	25	1
Very High	23	17	5	0
Uncertainty total		24	60	17
Semiarid types, Great Plains				
Sandsage (6501 km ²)				
Low	1	0	1	0
Moderate	15	0	10	5
High	27	13	14	0
Very High	57	56	0	0
Uncertainty total		69	26	5
Shortgrass Prairie (61,716 km ²)				
Low	4	0	4	0
Moderate	19	0	14	5
High	13	7	6	0
Very High	64	64	0	0
Uncertainty total		71	24	5
Shinnery Oak (5612 km ²)				
Low	0	0	0	0
Moderate	17	0	17	0
High	36	11	26	0
Very High	47	47	0	0
Uncertainty total		58	42	0

climate vulnerability forecasts. The hypotheses involved (Table 2) were aimed at understanding the value of the vulnerability surface in supporting subregional-scale analyses and climate adaptation strategies and in underpinning follow-on assessments (Hand et al. 2018).

Table 2. Ecosystem processes and hypotheses assessed for climate vulnerability.

Factor	Sample size (<i>n</i>)	Hypothesis
Wildfire severity (data years 2002–2011)	52,867	There is a positive relationship between vulnerability and burn severity driven by the accumulation of dead fuels in high vulnerability zones
Tree recruitment from lower life zones (data years 2005–2010)	1351	High vulnerability areas are more likely to have tree species indicative of downslope vegetation types
Encroachment of desert scrub into semidesert grassland (data years 2003–2006)	40,247	There is a positive relationship between vulnerability and increasing shrub cover

METHODS

Study area

The study area comprised the states of Arizona and New Mexico in the southwestern United States (Fig. 1). This area represents extraordinary vegetation diversity, with eight province-level ecoregions (Cleland et al. 2007) and a range of life zones from low desert to alpine. There are five broad climate regimes differentiated by seasonal precipitation and temperature patterns (Carlton and Brown 1983):

1. Winter precipitation-dominated, mild (mean soil temperatures $\geq 15^{\circ}\text{C}$)
2. Summer precipitation-dominated (monsoonal), mild (mean soil temperatures $\geq 15^{\circ}\text{C}$)
3. Winter precipitation-dominated, cold (mean soil temperatures $< 15^{\circ}\text{C}$)

4. Summer precipitation-dominated (monsoonal), cold (mean soil temperatures $< 15^{\circ}\text{C}$)
5. Semiarid—Summer precipitation-dominated, mean soil temperatures $\geq 8^{\circ}\text{C}$, high seasonal temperature variation (cold winters and hot summers)

Ecosystem types of mild climate are concentrated in the southern portions of the two states, while cold-temperate types occur across the Colorado Plateau of northern Arizona into northern New Mexico and at higher elevations (see Table 1). Vegetation of the semiarid regime of the Great Plains occurs mostly in northeastern New Mexico. Monsoon rains are concentrated in summer precipitation-dominated zones but affect the majority of the region and are expressed in the composition and seasonality of vegetation and in a fire season that averages much earlier than

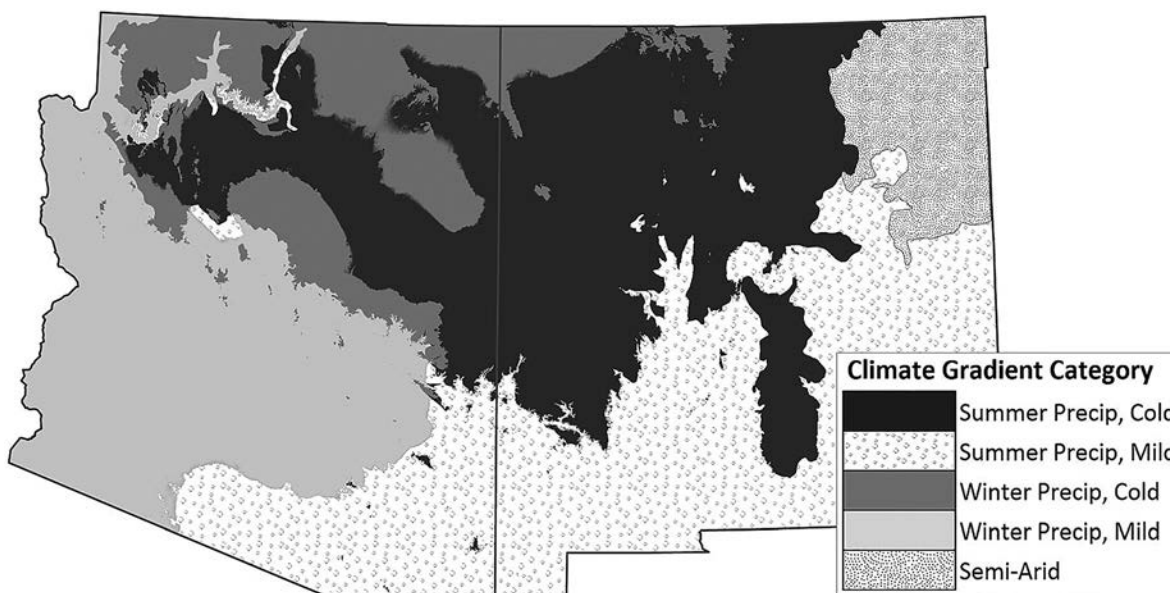


Fig. 1. Study area and approximate distribution of regional climate regimes (Carlton and Brown 1983).

most of the western United States (Evetts et al. 2008).

Assessment inputs

Spatial model base.—We required a spatial base map of 1:24,000 scale to accommodate imputation of fine-scale ecological data and downscaled climate information. To represent vegetation patterns at this scale, solar insolation data were used to build a polygon layer using eCognition, a horizontal analytics program that groups pixels of similar value and proximity into polygons (Definiens 2003). Insolation provides an inference of physical site variables including incoming energy, the primary driver for ecological processes and a strong predictor of vegetation potential (Dubayah and Rich 1995; Dubayah and Rich 1996, Triepke et al. 2008). Solar insolation values were derived from a *tri-shade* surface of the region, where each pixel was represented by growing season solar input as a computation of three sun angles in the spring, summer, and autumn (ESRI 2019). This resulted in a vegetation stand-scale configuration

of polygons of 10–20 ha in size to form the base units for our study (Fig. 2).

Ecosystem type mapping.—The USDA Forest Service developed ERUs to stratify landscapes ecologically for purposes of analysis, planning, and natural resource management (Moreland et al. 2017, Triepke et al. 2017). The ERU system represents broad biophysical themes of potential natural vegetation and historic disturbance regime (Daubenmire 1968, Barrett et al. 2010). Areas represented by a given ERU are united by patterns of natural succession, physiognomy, and community dominants. The ERU spatial dataset was compiled from several map sources including the Terrestrial Ecological Unit Inventory (TEUI; USDA Forest Service 1986, Winthers et al. 2005), Natural Heritage New Mexico mapping of Department of Defense and National Park Service lands (NHNM 2000), and from the Integrated Landscape Assessment Project (USDA Forest Service 2014).

We assigned the dominant ERU class to each polygon across the entire spatial domain and then developed climate envelopes for each ERU.

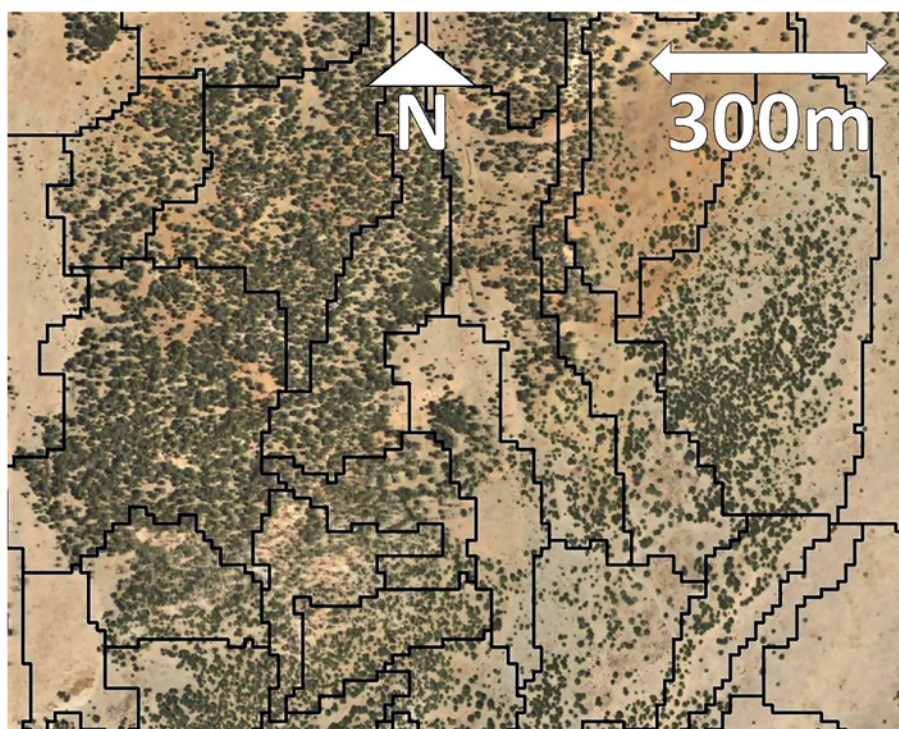


Fig. 2. A portion of the base polygon configuration with a backdrop of digital photography showing forest and grassland vegetation from the Zuni Mountains of western New Mexico (NAIP 2011).

In the process, we discovered the need to refine some ERUs to achieve normality for the climate variables used in the discriminant analyses and climate envelop modeling that followed. All map sources were overlaid with the regional polygon configuration, with ERU assignments given to each polygon according to majority value.

Climate models.—Downscaled climate model outputs for both pre-1990 climate and future climate were used to represent each polygon. Climate data were made up of over 20 temperature–precipitation variables including several unitless climate indices constituting combinations of temperature and precipitation variables (Rehfeldt 2006). Temperature variables are either in units of one-tenth degree Celsius, degree-days, or Julian date, representing annual or seasonal averages (e.g., mean annual temperature (MAT), mean maximum temperature in the warmest month, Julian date of first freezing). Precipitation variables are in millimeters and also represent annual or seasonal averages (e.g., mean annual precipitation [MAP], growing season precipitation). Climate indices included annual moisture index (ANNMSTIND), which equals the degree-days $>5^{\circ}\text{C}$ based on mean monthly temperature (DD5) divided by the MAP. The year 1990 corresponds with an asymptote in temperature and increased warming (Gutzler and Robbins 2010, Williams et al. 2013) and also reflects a point of diminishing returns of available meteorology station data as one goes further back in the record. Future climate data were from the CMIP3, the Climate Model Intercomparison Project, which is used to support periodic reporting by the Intergovernmental Panel on Climate Change (IPCC 2014). While these GCM outputs were available for years earlier than 2090, we opted for a maximal expression of warming of 2090 (i.e., decade average 2086–2095) so that managers could consider adaptation options that may not be realized for decades (e.g., tree species planting mixes that favor resilience of future forests).

The continent-scale resolution of the original GCM outputs (~310-km horizontal resolution; Joyce et al. 2011) necessitated downscaling to a spatial resolution of 90 m that was commensurate with the scale of ERU mapping and subregional assessment. For this purpose, we used climate data obtained from the Forest Service Rocky Mountain Research Station (RMRS; Rehfeldt

2006). This dataset included all GCMs available to us including CGCM3, GFDLCM21, and HADCM3 (IPCC 2007), with the A2 emissions scenario (higher emissions) available for all three scenarios and the A1B scenario (moderate emissions) available for CGCM3 (<http://forest.moscowfsl.wsu.edu/climate/>). The GCM outputs had been downscaled with the program ANUSPLIN (Hutchinson and Gessler 1994) per similar studies involving climate effects to vegetation (Rehfeldt et al. 2012). Spline climate modeling is as accurate as other interpolation methods such as kriging but more efficient to apply, with an advantage over PRISM and other regression methods for more precisely depicting downscaled climate values in complex terrain like that of the southwestern United States (NACSE 2013).

The final assessment results were based on the CGCM3 model and A1B emission scenario. This emission scenario was considered the most plausible balance of expected technological and energy development with the IPCC AR4 report and a standard representative for mid-range climate forcing and climate research (IPCC 2007, Gutzler and Robbins 2010). Agreement among the three GCMs (CGCM3, HADCM3, and GFDLCM21) at a given location provided an inference of uncertainty in the projection of future conditions. For the assessment of uncertainty, the A2 scenario was selected since it was the only scenario where RMRS data were available for all three GCMs. As with all climate variable values, the A2 values were imputed to each polygon based on the average of pixel values for A2 within the polygon (zonal mean).

It should also be mentioned that more recent GCM outputs became available late in the development of this study (IPCC 2014). The more recent climate projections of the CMIP5 assume the stabilization of CO_2 concentration, contrary to earlier skepticism about the stabilization of emissions-forced climate conditions by the late 21st century (Cole 2010). Both CMIP3 and CMIP5 indicate future warming in summer months beyond historic variation, though CMIP5 scenarios cover a greater range of future greenhouse gas concentrations that explain some differences in temperature and precipitation outcomes such as temperature extremes. Both sets of projections are similar in seasonal cycles of precipitation to suggest that the simulated trend is robust (Baker

and Huang 2014). We acknowledge the breadth of GCM outputs now available with CMIP5, though we maintain that CMIP3 remains valid for the Southwest given similarities between CMIP3 and CMIP5 projections along with our model validation results.

Site factors including aspect, slope, and elevation affect microclimate and suggest the need for multiple climate envelopes for any given ERU to accommodate a range of site conditions. This would have presented a substantial operational burden and issue for accuracy. To reduce noise and to avoid the need for a range of climate envelopes for each ERU, all temperature values were normalized to common energy settings (solar insolation) as a means of controlling for the variability in site factors. Formulae were developed for each ERU to relate energy and temperature variables so that all polygons could be calibrated to a common energy setting (Triepke 2017a). Using MAT to illustrate normalization, a scatterplot was generated to depict site energy (E , in $\text{kWh}\cdot\text{m}^{-2}\cdot\text{yr}^{-1}$) vs. MAT (tenths of a degree C) yielding the following linear equation:

$$\text{MAT} = 0.0676(E) + 80.238$$

A standard energy setting value was identified for the ERU by calculating the mean energy, $\bar{x}_E$, equal to $1934 \text{ kWh}\cdot\text{m}^{-2}\cdot\text{yr}^{-1}$. Using the mean, MAT values were normalized as follows:

$$\begin{aligned}\text{MAT}_{\text{NORMAL}} &= \text{MAT} - 0.0676(E - \bar{x}_E) \\ &= \text{MAT} + 0.0676(E - 1934).\end{aligned}$$

In this way, normalization was carried out for all temperature variable data. So for a particular site where energy was increased through normalization to the common energy setting, the temperature variable would be given a correspondingly lower value to offset the increase in energy. The formulae had the reverse effect on polygons where energy was reduced to the common setting. The overall implications of normalization were minor changes in temperature values relative to the initial values, but an important operational gain in answering the problem of myriad combinations of local site factors that would have necessitated multiple climate envelopes for any given ERU. It is important to stress that normalization of temperature variables did not alter the value of

temperature relative to precipitation since the variance of temperature data was not changed. At this point in the methods, each polygon of the two-state area had imputed values for ERU, pre-1990 climate, 2090 climate, departure of future climate, and uncertainty. The pre-1990 and 2090 climate data represented all climate variables, where temperature variables reflected only normalized values.

Climate variable selection

As with similar ecological applications (Williams 1983), discriminant analysis was used to identify optimal climate variables for class separation of ERUs—in our case for the purpose of developing climate envelopes and computing vulnerability and uncertainty scores. Discriminant analysis is an eigenanalysis technique that identifies the variables that yield maximum separation among predefined classes by the selection and weighting of input variables that maximally separate classes (McCune et al. 2002). Discriminant analysis carries four assumptions including homogeneity of variance within each class, normality of variables, linearity among all pairs of variables, and prior probabilities. Though homogeneity of variance is less important, we responded by excluding some ERUs with low sample numbers from the analysis. Normality was assessed one variable at a time. The assumption of linearity was not met and prior probabilities were unknown, as with most other ecological datasets where the assumptions of discriminant analysis are rarely realized (Williams 1983). Discriminant analysis was performed simultaneously for all ERUs with the outcome of identifying 5 of 21 climate variables, including some temperature variables, to construct climate envelopes as a comparative framework for analysis at subregional scales. Discriminant analysis was performed in Excel using the StatistiXL add-in package (StatistiXL 2007).

Samples for discriminant analysis were represented by individual polygons and were limited to extents with TEUI mapping, given the higher data quality of TEUI and the underlying rigor of fieldwork and photograph interpretation (Winthers et al. 2005). For some ERUs that were not adequately represented by TEUI (e.g., Intermountain Salt Scrub, ISS), the sample sets were supplemented by Natural Heritage New Mexico 0.04 ha

vegetation plot data (NHNM 2012). Combined, the two sources represent a sample area of ~15% of Arizona and New Mexico and lead to climate envelopes for all upland ERUs across the two states. To prevent under-sampled ERUs from exerting undue influence over the analysis results, all ERUs with less than an arbitrary threshold of 1000 samples were deferred from discriminant analysis (i.e., Alpine and Tundra [ALP], Bristlecone Pine, Chihuahuan Salt Desert Scrub (CSDS), ISS, Sandsage [SAND], Shortgrass Prairie [SGP]) but maintained in the overall vulnerability assessment.

Categorical climate variables were excluded due to their incompatibility with discriminant analysis. Two other variables, degree-days <0°C based on mean monthly temp and degree-days <0°C based on mean minimum monthly temp, were also excluded since these are based on freezing degree-days and many desert areas are represented only by zeroes. Pre-screening for the discriminant analysis resulted in a reduction in the total number of useable climate variables from 26 to 21.

Discriminant analysis was conducted iteratively: first, to winnow the number of climate variables and then to conduct stepwise sensitivity testing for determining the relative value of the remaining variables. In early iterations, all of the variables were assessed for normality leading to the elimination of some variables and to the subclassification of some ERUs to achieve normality (subclass results are not included in this reporting). We also explored different combinations of ERUs, on themes of life zone and temperature–precipitation regime (see Fig. 1) (Carlton and Brown 1983), to determine whether there were ERU-specific variables that may bring additional precision to envelope constructs. Potential redundancy among variables is addressed in discriminant analysis by tolerance, a unitless parameter for allowable redundancy for which we selected a tolerance threshold of 0.05, far more conservative than the default of 0.001. The outputs from StatisticaXL (StatisticaXL 2007) include a listing of the variables that do not meet the tolerance threshold and that can be left out of subsequent iterations. Per Rencher (1992), standardized coefficient output with discriminant analysis was used to quantify the explanatory value of each variable for climate vulnerability scoring.

Determining climate envelopes, vulnerability, and uncertainty

Using the optimal climate variables identified through discriminant analysis, climate envelopes were constructed for each ERU as a baseline for calculating future departure of climate to infer vulnerability. Vulnerability scores were determined for each polygon of the study area according to differences between the climate envelope of the polygon's ERU and the future climate at that location. Climate envelopes were represented by the sample mean and two standard deviations (SD, i.e., ~95% of the climate variability) following Comer et al. (2012). Ecological response unit climate envelopes and vulnerability scoring were developed with the following equation.

$$VS = \left(\frac{|\bar{x} - \text{Val}_{\text{seg}}|}{2s} \right) - 1 \quad (1)$$

where VS is vulnerability score for a polygon, $\bar{x}$ is mean of pre-1990 climate for one climate variable, Val_{seg} is year 2090 value for a given climate variable and polygon segment, and s is interannual SD of pre-1990 climate for the ERU.

This yields a unitless score for the level of departure of future climate from the climate envelope. The equation was formulated to yield a score of zero when, for a given polygon, conditions resulted in a calculation of exactly two SDs. A community at the mean of the envelope would have a score of -1 , while a community that exceeds the envelope by exactly two SDs (i.e., four SDs total) would result in a positive vulnerability score of one. Vulnerability categories were created to generalize results for resource management applications according to the number of SDs in future departure, either low (<2 SD), moderate (>2 and <3 SD), high (>3 and <4 SD), or very high (>4 SD). While this approach provides for a consistent computation and measure of departure among categories and ERUs, it also assumes proportionate climate impacts with increasing departure from one category to the next.

To take an example using the variable degree-days >5°C accumulating within the frost-free period (GSDD5), the vulnerability calculation for a given polygon whose climate envelope is represented by a mean GSDD5 of 1255.066, a SD of 322.896, and by a future GSDD5 value of 2701.464 is

$$\begin{aligned} VS_{GSDD5} &= \left(\frac{|\bar{x} - Val_{seg}|}{2s} \right) - 1 \\ &= \left(\frac{|1255.066 - 2701.464|}{2 * 322.896} \right) - 1 = 1.240 \end{aligned} \quad (2)$$

If the climate envelope of the ERU was based on GSDD5 alone as in Eq. 2, the vulnerability score for the polygon would be 1.240, that is, very high vulnerability. For the actual assessment, vulnerability was calculated as the combined departure for all optimal variables. By this approach, departure was calculated for each variable and then for all variables in combination, by weighting each variable according to its standardized coefficient (Triepke 2017a; Table 3). A composite vulnerability score was imputed to each polygon along with a vulnerability category representing the number of SDs departure. Composite calculations were made consistent by the way the departure Eq. 1 was structured so that the SD always yielded the exact same value (e.g., 0 for two SDs, 1 for four SDs). As a result, composite scoring was a simple matter of computing the weighted average of scores for each variable by the explanatory value expressed in their respective standardized coefficients.

With each GCM generating somewhat different results (Daniels et al. 2012), uncertainty was determined by the level of agreement among GCMs for the same locality and emission scenario. Uncertainty was scored by the following rules for each polygon: low uncertainty, outputs from all three GCMs yield the same vulnerability category; moderate uncertainty, outputs from two of the three GCMs yield the same vulnerability category; and high uncertainty, each of the

three GCMs yields a different vulnerability category. With this simple ruleset, uncertainty was computed and results imputed to each polygon.

Model validation and applications

Model efficacy was tested using independent data of real-world applications (Augusiak et al. 2014). The southwestern United States has experienced rapid warming in recent decades, making it a good testbed for evaluating climate model projections (Gutzler and Robbins 2010). To test the resulting vulnerability surface, we assessed the potential for climate forcing on ecological processes of the past decade from about 2000 to 2010, now well into the post-1990 projection period. The same vulnerability categories were used except that high and very high were combined into high+ for simplicity. We considered processes associated with global change and for which data are broadly available in the Southwest: wildfire severity (Eidenshink et al. 2007), recruitment of trees from lower life zones (Woudenberg et al. 2010), and the transition of arid grassland into desert scrub (Mellin et al. 2008; Table 2). In each case, we asked the question: Given similar environment, are there differences in the patterns of these processes with respect to the vulnerability categories? Chi-square analysis was used to compare observed and expected frequency values of ecological processes within each vulnerability category. Testing was limited to Forest Service lands given the geographic extent of available data to represent the ecological processes.

Testing for fire severity and shrub encroachment presented an operational challenge of processing multiple spatial layers in a GIS for a large extent (>8,000,000 ha). To make the process

Table 3. Final discriminant analysis results including the primary variables, tolerance, standardized coefficient, and relative explanatory value based on pre-1990 climate.

Variable	Tolerance	Standardized coefficient	Explanatory %
D100 (date sum of degree-days >5°C reaches 100)	0.287	1.193	26
DD5 (degree-days >5°C based on mean monthly temperature)	0.176	1.169	25
SMRMSTIND (GSDD5/GSP) (degree days >5°C accumulating within the frost-free period; growing season precipitation, April to September (mm))	0.342	1.015	22
WAHLIND (MAT/MAP)	0.551	0.658	14
MTWM	0.393	0.638	14

Notes: MAP, mean annual precipitation; MAT, mean annual temperature; MTWM, mean temperature in the warmest month; SMRMSTIND, summer moisture index; WAHLIND, Wahlberg annual moisture index.

Table 4. Deviation from expected and chi-square results for forest and woodland systems within mapped fire perimeters on Forest Service lands of Arizona and New Mexico in low, moderate, and high+ vulnerability categories.

Ecological response unit w/fire severity class	Deviation from expected (%)			<i>P</i>	<i>n</i>
	Low	Moderate	High+		
All				<0.00001	52,867
Non-lethal	-8.8	-2.7	7.7		
Mixed severity	0.9	2.8	-4.0		
Stand replacement	37.7	5.9	-25.9		
Spruce-Fir Forest				<0.00001	2364
Non-lethal	-29.2	-38.1	4.9		
Mixed severity	-33.8	-21.9	2.8		
Stand replacement	44.4	41.9	-5.4		
Mixed Conifer w/Aspen				<0.00001	5054
Non-lethal	-29.1	-6.9	48.2		
Mixed severity	-12.9	2.9	-11.8		
Stand replacement	53.5	6.1	-51.7		
Mixed Conifer-Frequent Fire				<0.00001	8639
Non-lethal	-34.9	2.4	22.7		
Mixed severity	1.4	-0.8	-0.3		
Stand replacement	72.2	-4.0	-47.8		
Ponderosa Pine Forest				<0.00001	14,132
Non-lethal	-16.7	2.4	5.6		
Mixed severity	20.5	-5.6	-3.5		
Stand replacement	91.0	-5.0	-40.6		
Ponderosa Pine-Evergreen Oak				<0.00001	3080
Non-lethal	26.2	0.1	-16.2		
Mixed severity	-45.6	1.3	25.7		
Stand replacement	-34.5	-6.4	32.1		
Pinyon-Juniper Sagebrush				0.81395	18
Non-lethal	n/a	-3.1	3.8		
Mixed severity	n/a	8.0	-10.0		
Stand replacement	n/a	n/a	n/a		
Pinyon-Juniper Evergreen Shrub				0.01955	3379
Non-lethal	3.4	0.2	-6.1		
Mixed severity	-8.5	-0.7	15.5		
Stand replacement	10.8	1.6	-21.7		
Pinyon-Juniper Woodland				<0.00001	2409
Non-lethal	-16.7	12.1	-1.1		
Mixed severity	42.4	-36.8	10.6		
Stand replacement	117.3	-14.5	-81.0		
Pinyon-Juniper Grass				0.00092	2304
Non-lethal	-4.4	-4.9	5.8		
Mixed severity	17.2	13.3	-16.6		
Stand replacement	-37.5	7.2	-1.6		
Juniper Grass				0.01130	433
Non-lethal	44.3	13.9	-4.6		
Mixed severity	-100.0	-41.3	13.2		
Stand replacement	-100.0	92.4	-22.7		
Madrean Pinyon-Oak				<0.00001	4766
Non-lethal	32.6	-12.1	3.7		
Mixed severity	-37.5	8.2	11.5		
Stand replacement	-40.6	33.6	-55.2		

(Table 4. Continued.)

Ecological response unit w/fire severity class	Deviation from expected (%)			<i>P</i>	<i>n</i>
	Low	Moderate	High+		
Madrean Encinal Woodland				<0.00001	6289
Non-lethal	−28.6	−13.9	16.7		
Mixed severity	30.7	23.3	−23.9		
Stand replacement	130.5	24.6	−48.1		

Table 5. Deviation from expected and chi-square results for shrub cover and climate vulnerability (low, moderate, and high), within the semidesert grassland ecological response unit on Forest Service lands of Arizona and New Mexico.

Shrub cover class (%)	Total <i>n</i>	Deviation from expected (%)		
		Low	Moderate	High+
<30	25,419	21.7	2.4	−9.3
30–59.9	12,816	−40.1	−2.4	14.8
60+	2012	−19.1	−15.0	23.8
All	40,247			

Note: *P* < 0.00001.

tractable, a point grid of 300-m spacing was used to generate sample sets while still allowing for large sample numbers (see Tables 4, 5). A spatial intersection of the sample grid was made with the vulnerability surface, fire severity mapping, and existing vegetation mapping to generate frequency values of these processes for chi-square analysis (e.g., frequency of stand replacement fire). Fire severity mapping was taken from the Monitoring Trends in Burn Severity archive to reflect fires in the Southwest >400 m in the previous ten years (Eidenshink et al. 2007). The MTBS is an ongoing satellite image classification program for mapping overstory vegetation mortality or topkill within all large wildfires of the United States, as either low, moderate, or high severity. Current shrub density was obtained from Forest Service existing vegetation mapping, which represents an image classification of shrub density from the mid-2000s (Mellin et al. 2008). We wanted to detect any significant differences in the overall amount of shrub density among vulnerability categories as a potential indicator of the influence of contemporary climate on the encroachment of desert scrub into grasslands, beyond the background effects of land use and fire suppression (Fletcher and Robbie 2004).

Testing for tree recruitment tree was based on late 2000s field sample data from the Forest Inventory and Analysis (FIA) database (Woudenberg et al. 2010), a repository of plot data that represents a probability sample of vegetation features on all forested lands of the United States. Using a GIS, FIA point samples were attributed by vulnerability category and then filtered to reflect the previous decade. Plots were further attributed by the ecological position of individual tree species present relative to the ERU—either typical, from above, or from below—according to constancy values provided in habitat type classifications for the region (Moir and Ludwig 1979, Hanks et al. 1983, Kennedy 1983, Alexander et al. 1984a, b, DeVelice et al. 1986, Fitzhugh et al. 1987, Muldavin et al. 1996). Two separate chi-square tests were performed based on the scenarios of from above and from below. Woodland ERUs were disqualified from the from below analysis since the next lower life zone is typically made up of grasslands of limited tree potential. Similarly, Spruce-Fir Forest (SFF) was excluded from the from above analysis as it occupies the uppermost life zone except alpine, also of limited tree potential. A chi-square test was applied to report deviation from expected and to compare observed and expected values among climate vulnerability categories.

RESULTS

Optimal climatic variables

After several iterations of discriminant analysis and improvements to the methods, five optimal climate variables were identified for building climate envelopes (Table 3). Of the five variables identified, three variables are associated with growing season warmth—Julian date that the sum of degree-days >5°C reaches 100 (D100), degree-days >5°C based on mean monthly

temperature (DD5), and mean temperature in the warmest month (MTWM)—the importance of which has been shown in other studies for vegetation in the western United States (Rehfeldt et al. 2006, Westerling et al. 2006, Williams et al. 2013). Also representing growing season conditions, the summer moisture index (SMRMSTIND) was the third-ranked variable, while the remaining variable, Wahlberg annual moisture index (WAHLIND), is also indicative of moisture conditions. The WAHLIND, a variable we derived for this study, relates the overall precipitation regime to MAT so that either higher temperatures or lower precipitation can accentuate WAHLIND values. Also, in the process of removing redundant variables (e.g., GROWRAT, MTWM) the relative influence of MTWM and DD5 on the discrimination of ERUs changed substantially, with DD5 having the second most explanatory value and MTWM becoming fifth-ranked. The DD5 is shown to be a useful variable in envelope modeling for vegetation species (Rehfeldt et al. 2006). The discriminant analysis made evident the values of specific variables in developing the climate envelopes.

Results were stable across iterations of discriminant analysis and among different sets of ERUs suggesting that outputs were robust for determining optimal climate variables. In particular, the D100 consistently placed in the top three variables for explanatory value. The SMRMSTIND and ANNMSTIND were also usually in the top three variables. Contrary to our initial assumption, these two indices exhibited strong tolerance and appear to be somewhat redundant and may be autocorrelated. Sensitivity testing showed that excluding one or the other of the two variables from analysis did not affect stability of the remaining variable or overall results so that ANNMSTIND was removed.

Analyses of the desert units were eventually stopped over concerns of the reliability of the resulting climate envelopes. Samples for the four desert ERUs (CDS (Chihuahuan Desert Scrub), CSDS, MSDS (Mojave-Sonoran Desert Scrub), and SDS (Sonora-Mojave Mixed Salt Desert Scrub)) were available only from the northern extents of the Chihuahuan and Sonoran provinces as they occur in the United States, in turn leading to envelopes that may be artificially constrained to favor the overprediction of

vulnerability. Also, these systems are especially resistant to stress, drought extremes, and to variability across temporal scales (Pockman and Sperry 2000, Enright and Miller 2007, Bhattachan et al. 2014). We deferred analysis of the desert systems and refer the reader to other recent vulnerability studies that include desert systems (Comer et al. 2012, Rehfeldt et al. 2012, Munson et al. 2013, Guida et al. 2014).

Assessing vulnerability and uncertainty

The vulnerability results indicate that only a small extent of the study area (6%) is projected to remain within its historic climate envelope by the year 2090 (Table 1; Fig. 3). Over 70% of the region was projected as high or very high vulnerability, with vulnerability patterns varying considerably among ERUs. Approximately half the study area was given an uncertainty estimate of low, with agreement among GCMs concentrated in the very high vulnerability category (43%). For most ERUs, a plurality of their extent falls within areas of moderate uncertainty. When combining low and moderate uncertainty categories (i.e., at least two GCMs in agreement), over 75% of the study area is represented.

Results show that the vegetation of upper life zones is at considerable risk to changing climate. Results for ALP affirm conventional perspectives on the most vulnerable ecosystem types, with all of the area modeled as very high vulnerability and as low uncertainty. Alpine is inherently vulnerable to warming given its limited extent at the southern periphery of its range in the United States, and given that most of the ERU is concentrated nearer the lower, warmer end of the life zone, making it susceptible to even minor temperature increases. Spruce-Fir Forest is less vulnerable than other upper life zone types, though is considerably vulnerable in southwestern and western extremities of the region. Nearly all of the Bristlecone Pine ERU occurs as high or very high vulnerability and as low uncertainty. In contrast to the other upper elevation systems, the Montane/Subalpine Grassland (MSG) had the lowest overall vulnerability of any ERU.

At middle elevations, the two major montane forest units—Mixed Conifer-Frequent Fire (MCD) and Ponderosa Pine Forest (PPF)—exhibit lower vulnerability than upper elevation systems, with each ERU having half or less of its

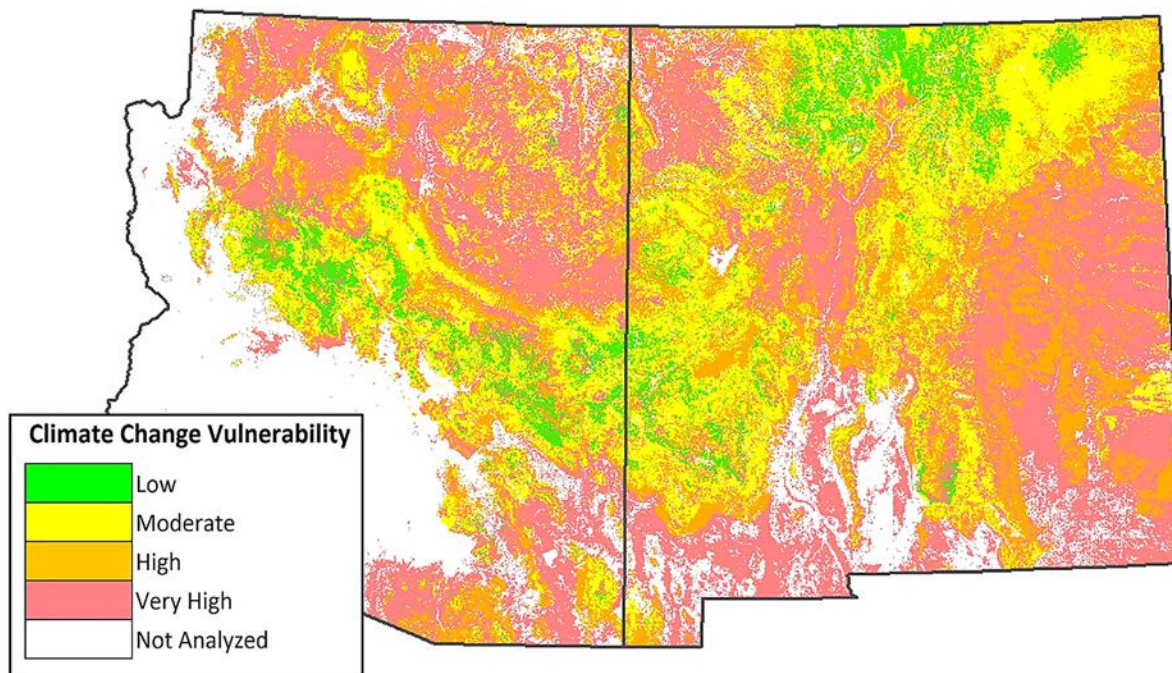


Fig. 3. Patterns of climate vulnerability within the study area of Arizona and New Mexico. Vulnerability is categorized as low, moderate, high, and very high.

area in high to very high vulnerability. However, vulnerability increases significantly for these ERUs as one moves southward in either state (see Fig. 4, PPF).

Among the woodland ERUs, Pinyon-Juniper Sagebrush (PJS), a cold-temperate type, had the greatest vulnerability with the vast majority occurring as high or very high vulnerability in combination with low uncertainty. In contrast, Pinyon-Juniper Evergreen Shrub, which occurs to the south under mild temperature regimes, had the lowest vulnerability of the woodland ERUs (Fig. 4). The two Madrean woodland units of mild extents, Madrean Pinyon-Oak and Madrean Encinal Woodland, stand in contrast to one another at 37% and 75% high or very high vulnerability, respectively.

Grasslands make up nearly 40% of the region with most grasslands represented by semidesert grassland (SDG), Colorado Plateau/Great Basin Grassland (CPGB), and SGP, collectively comprising much of the low-lying valley and plains among islands of mountain topography. High and very high vulnerability categories make up

more than 75% of each of these ERUs. An associate of valley bottoms and plains, the ISS had the highest vulnerability of any shrubland system, a reasonable expectation for an ERU at the southern edge of its range and despite the hardiness of salt scrub systems (Blaisdell and Holmgren 1984). Results for these ERUs of broad intermountain expanses also reflect the lowest uncertainty.

Of the other shrubland systems, SAND had the greatest vulnerability. In contrast, the Interior Chaparral had the lowest vulnerability, consistent with its affinity toward mild climate regimes. For the Shinnery Oak (SHIN) ERU, our results suggest that it is substantially more vulnerable than most other ERUs, similar to results for other Great Plains systems (SAND, SGP). And like SGP, southeastern New Mexico represents the southern extent of SAND range. Sagebrush Shrubland (SAGE) had the lowest vulnerability of shrubland types and stood in contrast to the vulnerability forecast for other cold-temperate ERUs at their southern limits.

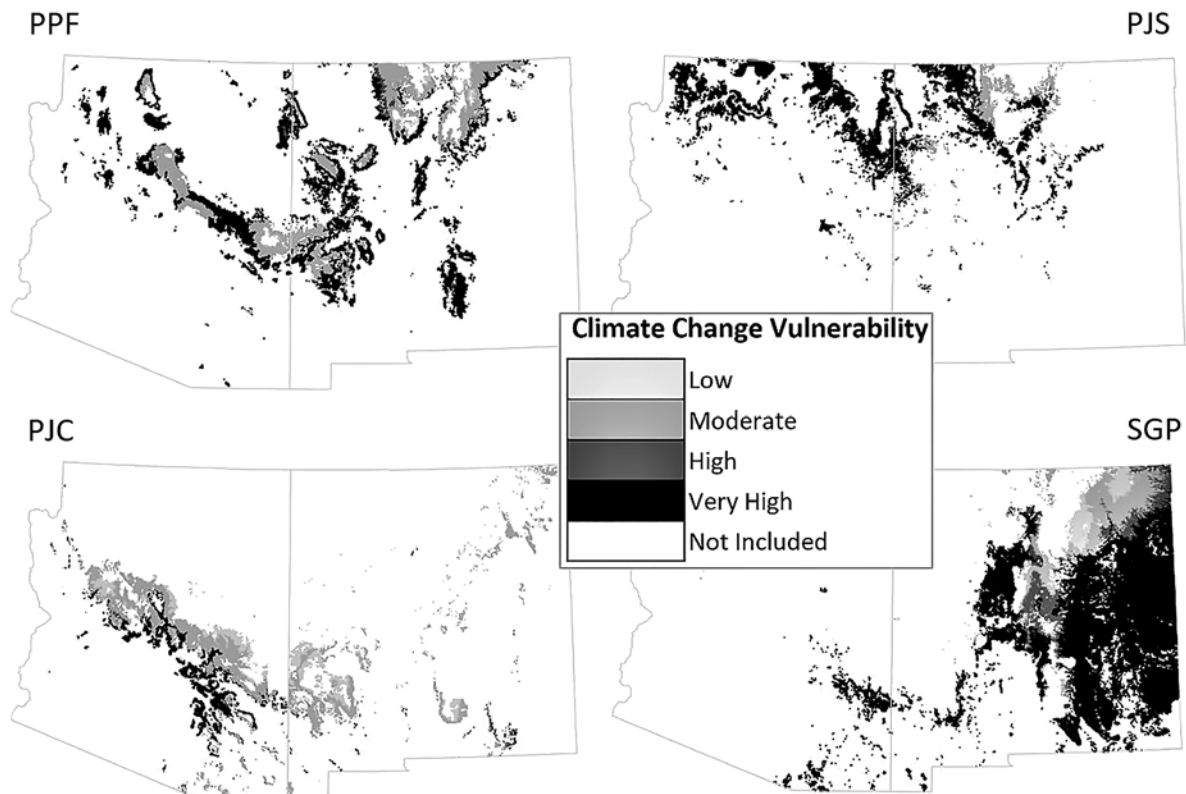


Fig. 4. Spatial distribution of climate vulnerability for four representative ecological response units including Ponderosa Pine Forest (PPF), Pinyon-Juniper Sagebrush (PJS), Pinyon-Juniper Evergreen Shrub (PJC), and Short-grass Prairie (SGP).

Model validation and applications

Our analysis of fire severity patterns in forests and woodlands indicates a significant *inverse* relationship between severity and climate vulnerability for most ERUs. Of particular interest to Southwest land managers is stand replacement fire, the most destructive severity class, where the observed frequency in low vulnerability areas was over a third of that expected for all forests and woodlands combined (Table 4). The findings were corroborated in areas of high+ vulnerability where the frequency of stand replacement fire was much less than expected.

Analysis results for recent scrub encroachment into the SDG indicate a significant positive relationship between shrub cover and climate vulnerability (Table 5). The findings were consistent with the hypothesis that high vulnerability zones

will favor the encroachment of desert scrub to a greater degree than low vulnerability areas, all else being equal. Results suggest that high vulnerability areas were nearly 24% more likely than expected to have shrub canopy cover values over 60%.

When analyzing the recent tree recruitment from lower life zones, we found that only 8% of FIA samples exhibited tree recruitment abnormal for the ERU; that is, for most sites, there has been little recent growth of species from below (lower elevations) or from above (higher elevations). But among the samples with abnormal tree composition, sites in high+ vulnerability zones were significantly more likely to have downslope tree species than either low or moderate vulnerability areas (Table 6). Similarly, low vulnerability areas were much more likely to show recruitment of upslope species.

Table 6. Deviation from expected (%) and chi-square results for tree species recruitment from upper and lower life zones, an analysis of Forest Inventory and Analysis samples from forest and woodland systems of Arizona and New Mexico.

Tree recruitment	Total <i>n</i>	Expected			Deviation from expected			<i>P</i>
		Low	Moderate	High+	Low	Moderate	High+	
From above	49	21.3	45.2	33.5	63.4	37.0	−64.8	0.00074
From below	68	14.7	44.0	41.3	−90.4	−62.5	98.7	<0.00001

DISCUSSION

Optimal climate variables for characterizing variation

Discriminant analysis proved a useful tool for identifying climate envelope variables among ERUs and for evaluating their relative importance. Precipitation variables had low discriminatory value implying that the climate separation of ERUs bears more on temperature than on precipitation. Despite the value of precipitation in previous species envelope modeling (Rehfeldt et al. 2006), the best performing precipitation variable in our study was MAP which captured only 7–10% of the explanatory value. The poor performance of precipitation variables may also be a function of the marked geographic variability in seasonal precipitation across the Southwest. The greater reliance on temperature variables may indicate a more robust model, given the greater uncertainty in precipitation forecasts relative to temperature (Cayan et al. 2013). Nevertheless, precipitation is still represented in the primary climate variables with the SMRMSTIND and the WAHLIND. The inclusion of SMRMSTIND was somewhat subjective given our desire to express growing season precipitation as a critical element for the climate effects anticipated for Southwest landscapes (Gutzler 2013, Williams et al. 2013). Degree-days >5°C based on mean monthly temperature (DD5) and MTWM may have particular importance given the effect of increased summer temperatures on vapor pressure deficit and observed tree mortality and fire behavior in the western United States (Westerling et al. 2006, Williams et al. 2013). Our climate envelopes may be conservative in that they do not account for processes such as the exponential relationship of moisture deficit with increased summer temperatures, multi-year drought, and changes in the seasonality of

precipitation or snowmelt (Weiss et al. 2009, Serfat-Capdevila et al. 2011).

Vulnerability assessment

Overall vulnerability patterns for the Southwest suggest remarkable change, with a substantial amount of every ERU projected to exceed characteristic climate envelope conditions. It is important to stress that vulnerability in the context of this study involves likely changes in predominant vegetation features as inferred by the departure of future climate from pre-1990 envelopes. In broad terms, it may be helpful to think of future climate as a potential stressor of significant change (i.e., on structure, composition, process) with vulnerability scores on par with the probability of type conversion. The vulnerability scores themselves stem from three factors including: (1) the pre-1990 climate status at a given location relative to its ERU envelope, with the site alternatively vulnerable (e.g., warm-dry end of the climate envelope) or insulated (e.g., moist-mesic end of the climate envelope) to climate change; (2) magnitude of the projected change in climate at that location, since projected changes in temperature and precipitation across the region are not uniform; and (3) the breadth of the envelope for a given ERU, given that the breadth of climate envelopes among ERUs was similar but not equal. These factors provide an underpinning for the interpretation of vulnerability results for a particular area and ERU.

Results for individual areas such as a National Forest show that model outputs vary considerably across the region. In some areas, a given ERU may be inherently susceptible to change and broad-scale controls if it is already concentrated at the warm-dry margin of its climate envelope (Gosz et al. 1992). Conversely, the ERU may elude vulnerability if occupying more mesic extents as appears to be the case for the SAGE in

northern New Mexico. Yet, by our assessment most natural communities of the region are susceptible to fundamental change in vegetation composition and structure. In particular, the cold climate ERUs existing at their southernmost extents in North America are at risk of regional extirpation. Even the best cases such as SAGE, with the resilience that one might expect of an arid system, is expected to be significantly vulnerable over two-thirds of its area.

Vulnerability results for representative ERUs of forest, woodland, shrubland, and grassland ecosystems were consistent with latitudinal patterns that one might expect (see Fig. 4). For example, montane forests, represented by both PPF and MCD, showed similar patterns of reduced vulnerability with latitude in the transition from mild to cold regimes. For the conterminous United States, Rehfeldt et al. (2012) likewise projected that only about 25% of montane conifer systems would be remaining in their current location by 2090. The PPF is particularly vulnerable in the southern extremities of its range in Arizona and New Mexico where it occurs in island mountain ranges surrounded by desert and plains. This is corroborated by large swaths of stand replacement fire area, such as those in the Sacramento Mountains of south-central New Mexico, that have ostensibly converted montane forests in recent decades to juniper or shrub cover types. Areas of lesser vulnerability are concentrated in north-central New Mexico for both ERUs as with many other ERUs including PJ Sagebrush and Gambel Oak Shrubland, where high vulnerability is otherwise ubiquitous. High vulnerability areas of PJ Evergreen shrub on the other hand were concentrated over a smaller proportion of the ERU, mostly in central Arizona below the Mogollon Rim. Areas of high vulnerability in SGP were focused in extremities and disjunct extents of the Great Plains that extend to southeastern Arizona. This coincides with a northward trend for the Great Plains projected by Rehfeldt et al. (2012). Refugia may exist in north-central New Mexico for some ERUs at their southernmost extent due to the lower overall vulnerability of this area.

It falls to land managers to consider the vulnerability and geography of each ERU, the ecosystem services they provide, and then to work across multiple jurisdictions and landscapes to

optimize the strategies of both resistance (preservation) and climate adaptation. Also important are the limitations of the assessment and the necessary caveat that model outputs are not intended for the evaluation of individual polygons. Rather, the vulnerability surface is suited for mid-scale and broader applications where results are summarized to large reporting areas such as watersheds, Wilderness areas, administrative units, and similar extents. For illustration, Fig. 5 shows vulnerability patterns at the mid-scale for the Gila National Forest in southwestern New Mexico. Notice that MCD appears most vulnerable at its lowest elevations of the Gila mountain ranges as would be expected for the warm-dry ecotone of a vegetation type. The mapping also suggests that active management aimed at resistance or at adaptation and realignment could be focused where road access exists in contiguous areas of mixed conifer in the lower half of the Forest. Fig. 5 also shows the vulnerability of Pinyon-Juniper Grass (PJG) in areas of the Forest to the south and southwest. Low vulnerability, on the other hand, exists in smaller areas to the north that may suggest the opportunity for restoration and management of these localities as refugia.

The vulnerability assessment can underpin strategic planning for guiding project work but must be corroborated at the site level by local practitioners for signs of climate stress such as mortality. The vulnerability assessment should also be complemented with a fuller picture of local circumstances such as disturbance history, water inputs, presence of invasive vegetation, and the adaptive capacity of plant dominants (Handler et al. 2017).

Applications and efficacy of the vulnerability assessment

The results of our validation relating vulnerability with key ecological processes indicate some initial effects of warming temperatures on vegetation within the post-1990 period, both corroborating and contradicting our initial hypotheses (see Table 2). The inverse relationship that we discovered between vulnerability and fire severity repeats across most of the forested ERUs and regardless of spatial scale, holding even in the case of the individual fire areas that were examined with our initial investigations. Initially, we

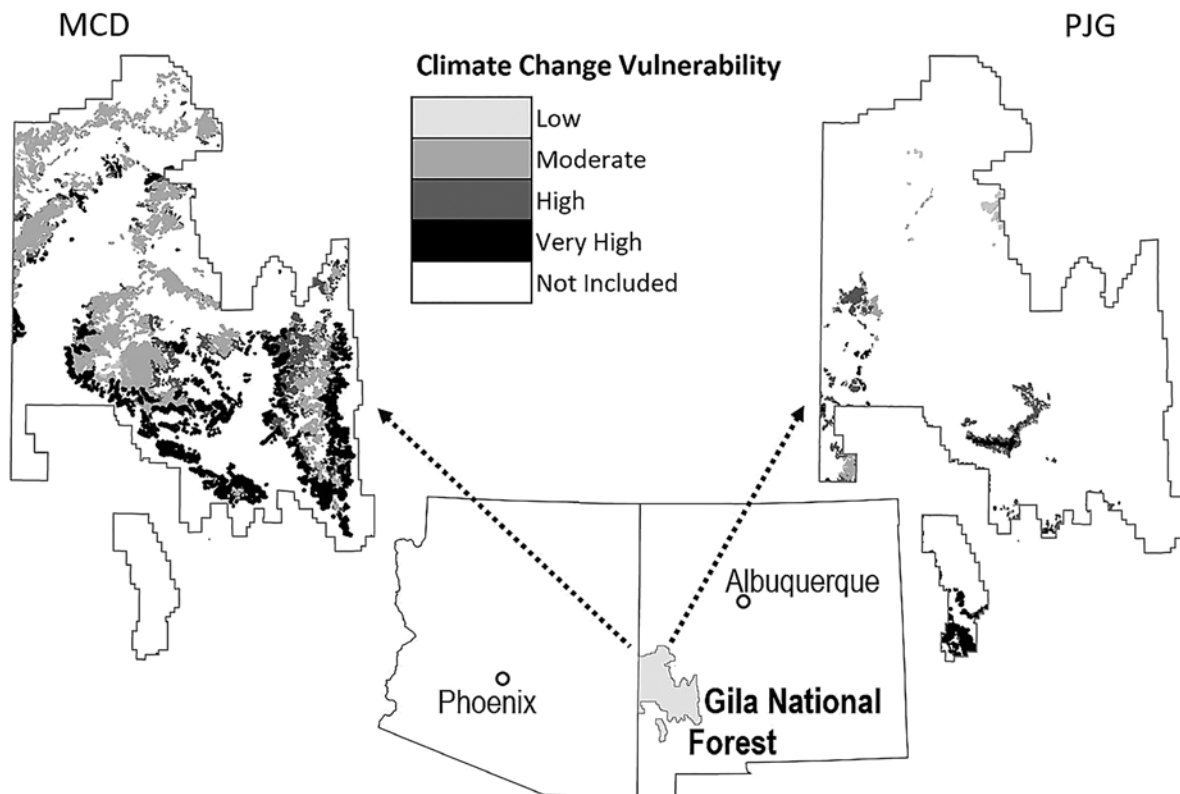


Fig. 5. Spatial distribution of climate vulnerability on the Gila National Forests for two representative ecological response units, the Mixed Conifer-Frequent Fire (MCD, left) and Pinyon-Juniper Grass (PJG, right).

controlled for past land use by considering the relationship between stand density and subsequent fire severity expressed in our data (P -value < 0.00001) and as shown by others (Finney et al. 2005). Yet, the overall pattern of severity and vulnerability held either way, and sample numbers and overall significance were improved without stratifications for stand density or tree size class.

There are possible exceptions to the inverse relationship between fire severity and vulnerability. For example, PJG shows negative values for stand replacement fire for both low and high vulnerability conditions; however, inconsistencies may be explained by low sample numbers in individual strata as in the case of PJG samples that occur in stand replacement fire areas of low vulnerability ($n = 2$). Results for PJS and Juniper Grass are likewise questionable due to low sample numbers, particularly for PJS where results were not significant ($P = 0.81$). Ponderosa Pine-Evergreen Oak (PPE) was the notable exception

to the inverse pattern of severity and vulnerability. Sample numbers for PPE varied for severity-vulnerability strata, ranging between 27 and 996 ($P < 0.00001$). But based on the results overall, it is worth considering an alternate hypothesis involving potential relationships of vulnerability, productivity, fuels, and fire: High vulnerability, reduced soil moisture, and higher evaporative demand may correspond to reduced productivity, fuel abundance, and fire risk (Rocca et al. 2014). The alternate hypothesis that reduced plant productivity is an indirect expression of warmer-drier conditions has been supported by Parks et al. (2016). In their analysis of recent wildfires in the western United States, the authors showed a positive relationship between fire severity and MAP, and a negative relationship with water deficit, both results inferring a linkage with plant productivity and fire that could be expected under future climate in the Southwest. More investigation is needed to

determine the role of fuel conditions and vulnerability in influencing fire severity and differentiating variables associated with the increasing number of extreme wildfire events that are characterized by unusual fire behavior, spread, and suppression difficulty (Tedim et al. 2018).

In terms of tree migration, there was an apparent preference for the recruitment of downslope tree species (from below) into high vulnerability settings. The results suggest a disparity in recruitment between low and high vulnerability settings and help substantiate the theorized upward migration of plant species under warmer climate conditions. Other studies have convincingly demonstrated similar elevational patterns for the southwestern United States (Allen and Breshears 1998, Brusca et al. 2013, Guida et al. 2014). For upslope tree species, the results also support vulnerability expectations—upslope tree species are far more likely to regenerate in lower vulnerability habitats. With additional exploration and accumulation of FIA data, scientists can more carefully assess elevational dynamics of tree species as others have explored for latitudinal dynamics (Iverson and Prasad 1998, Zhu et al. 2012).

Results of the analysis of shrub encroachment into SDG reveal that increased shrub cover was more likely in high vulnerability settings, consistent with our hypothesis that vulnerable communities are more susceptible to grassland-to-scrub conversion, all else being equal (land use). There are numerous characterizations of the global pattern of arid grassland transitioning to desert scrub stemming from disturbance history (Buffington and Herbel 1965, Dick-Peddie 1993, Archer et al. 1995, Huenneke et al. 2002, Valone et al. 2002, Briggs et al. 2005, D'Odorico et al. 2012, Caracciolo et al. 2016). Repeat monitoring with the support of existing vegetation mapping (Mellin et al. 2008), National Land Cover Data (Homer et al. 2007), National Ecological Observatory Network (Keller et al. 2008), the Long Term Ecological Research Network (Waide and Thomas 2013), and other systematic national and regional inventory, monitoring, and assessment programs are vital for quantifying and reporting climate and drought effects to natural systems.

Finally, for a given hypothesis we expected chi-square results to follow a sequence of magnitude from low to moderate to high+

vulnerability. Indeed, chi-square results for fire severity overall (and for the majority of ERUs individually), tree recruitment, and scrub encroachment revealed that moderate vulnerability always held the middle value, between low and high+ vulnerability, a pattern that in itself helps to validate the strength of vulnerability assessment results and the value of downscaled climate modeling.

CONCLUSION

By optimizing spatial and thematic resolution and by minimizing sources of potential error, we were able to generate a vulnerability surface of high resolution and comprehensive coverage to advance an approach to climate vulnerability assessment suitable for local planning, analysis, and management. The modeling approach is portable to other areas of the world that have the essential data inputs—high-resolution climate surfaces, downscaled GCM outputs, and accurate mapping of ecosystem types. Where quality mapping is not readily available, suitable mapping can be built by augmenting the approach of Holdridge life zones (Holdridge 1947, Lugo et al. 1999) as others have done to assess climate vulnerability (Enquist 2002). While our approach provides more thematic and spatial detail than other assessments, it does not project the future distribution of extant or of no-analog ecosystem types, let alone actual manifestations such as tree dieback, species range shifts, extinctions, or other impacts. We opted against mechanistic models that integrate disturbance and other processes as complicating factors, knowing that it is a matter of when, not if, areas in high vulnerability will undergo significant change by agents such as uncharacteristic fire acting as accelerators of predisposed outcomes. Despite the good separation among our climate envelopes, we opted against modeling the future geographic distribution of ERUs for the many intractable complexities mentioned, not to mention the necessity for additional inputs (e.g., soils) and the likelihood of additional error. Others have provided such analyses at broader themes and geographic scales appropriate for this type of vulnerability assessment (Rehfeldt et al. 2006, 2012, Notaro et al. 2012). Proactive management may not be about planning for some future landscape

pattern as much as it is about helping existing ecosystems cope with probable change through improving adaptive capacity (Millar et al. 2007).

We offer a subregional-scale climate vulnerability assessment based on global climate model projections to inform resource managers at operational scales approaching individual basins or watersheds, providing a meaningful context for local and necessary on-the-ground interrogation of sites for management prescriptions. That is, results from this type of assessment can be used to underpin an adaptation strategy and then be combined with knowledge of local conditions and plant functional traits to narrow and prioritize the range of adaptive management options (Handler et al. 2017). In some scenarios, adaptation efforts will be concentrated in landscapes of high vulnerability and low uncertainty for a given ecosystem type. For example, thinning and prescribed burning in areas of woodland savanna that have been substantially altered from their reference conditions may reduce the risk of catastrophic disturbances, improve adaptive capacity, and facilitate the realignment of vulnerable areas. Similarly, in high vulnerability zones affected by wildfire, forest practitioners may opt to focus tree planting at the upper ecotones or alternatively plant tree species of lower life zones at the bottom ecotone. Range managers may wish to defer restoration and resource expenditures for vulnerable arid grasslands where climate forcing indicates a transition to desert scrub. In all cases, outputs from the vulnerability assessment can be linked to an overall strategy as part of a useful operational framework for meeting the challenges of managing landscapes in the changing climate of the 21st century.

ACKNOWLEDGMENTS

We are grateful to the Forest Service's Western Wild-land Environmental Threat Assessment Center and to Deborah Finch of the RMRS for their resources and support and for a mind to the future of conservation in the region. We also thank Wayne Robbie, Steve Stren-ger, George Robertson, and all members of the TEUI program for field data and for information relating vegetation and climate. We are also grateful to the For-est Service Geospatial Technology and Applications Center for the development of the segmentation layer and to Nick Crookston of the RMRS Moscow

laboratory for several climate data deliverables. We acknowledge key members of the regional Forest Ser-vice staff including Bob Davis, Candace Bogart, Kath-leen Hawkos, Rick Crawford, and others who have given assistance and their commitment to this study. We thank Scott Collins, Dave Gutzler, and Tim Lowrey for their helpful comments on the manuscript.

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