Applying New Science to Develop a Collaborative Decision Support System for Forest Management in the Southern Sierra Nevada

Conservation Biology Institute

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Introduction

Land managers in the southern Sierra Nevada need better decision-support tools to address unprecedented forest resilience challenges resulting from climate change and previous management actions, especially forest fire suppression. Overstocking of trees, historic drought, and a dramatic increase in the size and severity of wildfires have resulted in extensive tree mortality across the range over the past decade. Wildfires are burning in novel climate conditions on a landscape stressed to the point of large-scale tree mortality and type conversion.

Managers must make crucial decisions regarding the allocation of limited fuel reduction resources, knowing their decisions are often based on incomplete information and outdated models. And, while much attention is rightly paid to reducing stand densities that contribute to tree stress and fire intensity, emerging science strongly suggests that managers also need to consider how stand structure, terrain, and prevailing weather conditions affect oxygen flow to fires, the potential for fire-atmosphere coupling, and the emergence of massive “megafires” that are becoming increasingly common and destructive (Coen 2018, Coen et al. 2020, North et al. 2022, Stephens et al. 2022).

This project addressed the need for regionally-relevant forest management decision support tools by developing new models and maps of severe wildfire risk and drought-related tree mortality in the southern Sierra Nevada. The models include multivariate statistical models of drought and fire risks, and transparent modular models using the fuzzy-logic modeling system, EEMS (Ecosystem Evaluation Modeling System (Sheehan and Gough 2016)). The statistical models used the best variables and data available at the time of the project to provide recent snapshots of forest conditions and were used to inform development of the updateable EEMS models to be used in decision-making. The EEMS models of forest resilience rely on variables and datasets that can be updated to reflect environmental change.

This project also developed a method of using statewide forest structure data from the California Forest Observatory (CFO) (California Forest Observatory 2020)) to calculate vegetation-created wind-drag at 10m horizontal and 1m vertical resolution based on how trees, shrubs, and ground cover affect winds below, within, and above forest canopies. These vegetation-based wind-drag coefficients can be used to calculate how oxygen flow to fires is affected by forest structure and thus affects fire behavior. Changes in forest structure, for example due to fires or fuels treatments, may affect fire behavior and the likelihood of extreme wildfire behavior induced by atmosphere-fire coupling (Coen et al. 2020). Because CFO data are California-wide and were expected to be annually updated, wind-drag maps could be updated annually and used to guide fuel-treatment priorities. These results can be immediately applied to improving assessment of the effects and effectiveness of fuels treatments using operational fire models, which to date have not accounted for how reducing fuels also increases ventilation (e.g., FlamMap 6.2). Although the scientific consensus has been that fuels treatments reduce fire intensity within the treatment footprint, it is essential to understand and quantify how they may also increase ventilation into neighboring areas, and hence potentially increase fire risks in unintended ways.

Combining vegetation effects on wind drag with the effects of terrain and weather can greatly improve our understanding of where and under what conditions severe fire behavior is most likely to develop, and thus improve siting and design of fuels treatments to be most effective. Landscape wind-drag maps that consider how vegetation, terrain, and climatology affect fire winds can be used to map where rapid fire spread and crowning behavior are most likely to occur. For example, analyses of recent megafires using forensic super-computer models, such as the Kings Fires, illustrate where terrain alignment with prevailing winds can funnel oxygen flow to create extreme fire behavior (Coen et al. 2018).

Science Team

The project was guided by a team of scientists that met regularly during the project to formulate approaches, identify useful data sources, and discuss how best to apply emerging fire science to understanding forest resilience. The Science Team combined expertise in forest ecology, ecological modeling, the physics of fire behavior, and mathematical approaches to modeling complex phenomena. Team members provided guidance, support, and data for the model designs and inputs.

Science Team Members:

- Wayne Spencer, CBI, Principal Investigator
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- Malcolm North, USFS
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- Christopher Anderson, Salo Sciences
- Christopher Wikle, University of Missouri
- Adrian Das, USGS

Literature Review

The Project Team collected and reviewed scientific and gray literature to inform discussions with the Science Team, and to ultimately inform model development. See **Appendix A: Relevant Knowledge Resources for the Sierra Nevada Resilience Project - Publications** for a complete bibliography.

Data Acquisition and Assessment

A broad review of 44 data sources, many of which provide multiple data outputs, was conducted early in the project. See **Appendix B: Relevant Knowledge Resources for the Sierra Nevada Resilience Project - Data and Models** for an annotated listing.

The project team decided to prioritize use of datasets from the California Forest Observatory and Sierra Nevada Regional Resource Kit, because these are expected to be regularly updated into the future with support from state and federal agencies to allow for regular model updating and refinement as conditions change and new data come online. The methods section below lists datasets from these sources that were evaluated and used for each of the models.

We decided from the beginning of the project to rely heavily on forest structure data provided by the California Forest Observatory (CFO; Salo Sciences 2020) in statistical analyses and especially for use in the decision support system. Like many agencies, we thought CFO represented the best available scientific dataset of forest structural conditions that fully covered the study area (and beyond) and would be regularly updated with agency support as forest conditions change. This is exactly the sort of data needed for a forward-looking decision-support system of forest resilience. However, we discovered important inaccuracies, inconsistencies, and idiosyncrasies during our attempts to apply these data in our models and calculations, such as canopy base heights greater than tree height ("upside-down trees") or ladder fuels where there is no canopy above shrubs or small trees. We therefore needed to develop work-arounds by carefully selecting and intersecting variables using GIS overlay analyses to correct for inaccuracies. For wind-drag calculations, we needed to develop specific mathematical corrections, as described in **Appendix C - Correcting California Forest Observatory Forest Structure Metrics for Wind-drag Calculations**, which also offers recommendations for systemically correcting these issues in future CFO releases. We still believe that the CFO system is valuable for tracking and predicting forest conditions, but also that users need to be aware of pitfalls in using the datasets as they currently exist.

Statistical Models

Statistical correlation and machine-learning methods have been successfully employed to model and map the spatial distribution of fire ignition locations, locations of large wildfires, and fire occurrence and to illuminate the relationships and importance of drivers of these phenomena, which vary across regions and ecosystems. Understanding these relationships is key to building decision-support systems and planning effective management actions.

Similar to species' distribution models, this approach associates observations of the response variable of interest (e.g., ignition locations) with mapped environmental predictor variables to evaluate the relative influence of each predictor variable on the known occurrences of the response variable. The resulting highest-ranking predictor variables are then used to create a quantitative model and produce a continuous map of relative probability of the response variable's occurrence in the future based upon the factors and processes unique to the region.

CBI used this methodology to create statistical and machine learning models and maps of severe wildfire probability and forest drought vulnerability in the study area, conditioned upon large suites of variables known to be associated with their distributions. Through these models, CBI also quantified the relative importance of different environmental factors associated with high fire severity and drought vulnerability. The output of this analysis includes the stand-alone statistical models in addition to information used as input to the EEMS modeling and decision-support system. The map outputs were examined in comparison with statewide datasets and expert knowledge with the Sequoia Regional Partnership stakeholders in several model review meetings. The statistical models helped inform EEMS variable selection and importance (weights), model structure (sub-branches/nodes based on predictor interactions), response types (conversion functions) and thresholds. The maps based on statistical models are also valuable as regionally-specific projections of these threats to be used in addition to other available Sierra-wide and state-wide maps.

Methods

Based on a thorough review of recent literature concerning environmental drivers of the spatial and temporal patterns of fire severity and drought-related tree mortality in Sierra Nevada forests (Appendices A and B), we identified potential data sources for defining explanatory variables (e.g., forest structure, terrain, climate, fire history) and response variables (e.g., tree mortality, fire severity) to use in statistical models (Appendix E). We also performed an analysis of fire and extended drought history to ensure we could attain mapped data representing the appropriate dates or date ranges for associating the response variable with the explanatory variables. We downloaded and compiled all pertinent mapped response and explanatory variables and processed them into appropriate formats for modeling (Appendix E - Statistical Model Data Sources).

For our fire severity response variable, we used the Composite Burn Index (CBI, a Landsat-based burn severity metric) projected across the Sierra Nevada region using 2017-2022 ground conditions. We calculated CBI using a script provided by Parks et al. in Google Earth Engine (https://www.mdpi.com/2072-4292/13/22/4580). Our input to the script included 8,331 sample points from 558 fires spanning 2010-2020.

For the drought vulnerability response variable, we extracted data from 10,000 sample points distributed across maps of forest drought die-off and unattributed browning from 2015-2017 (Wang 2021, Wang et al 2022). Because effects of the 2012-2016 drought (e.g., tree mortality) peaked during the period 2015-2017, we tested and compared model performance using different sets of pre-drought variables from 2012-2014 as predictors. Based on the results of that comparison, we settled on using 2014 to represent pre-drought conditions unless a particular variable was not available for that year, in which case we selected the most recent year available.

For both the fire severity and drought vulnerability models, we explored a wide range of potential predictor variables, with some derived using various spatial and temporal windows of measurement as well as different summary statistics (e.g., minimum, mean, or maximum values). Our ultimate objective was to narrow the number of variables used to populate the models and decision support process to only those that are most important in controlling fire severity or drought vulnerability in the study area. However, we started with this large selection to ensure that, for each variable type or grouping of variables, we selected the most important correlate to represent the group.

For all pairs of continuous variables, we calculated correlation coefficients and identified all pairs with a correlation >= |0.70|. Our variable selection process first involved selecting the most important predictor from small, correlated groups of the same variable calculated in different ways (e.g., value extracted either at point location or from moving window). For several variables, we explored the relative importance of different temporal metrics of quantification and retained the variable with the highest independent importance to fire severity or drought vulnerability. For example, we calculated mean annual and 30-year normal values for a range of climate variables (e.g., mean annual or 30-year normal temperature or precipitation), compared their relative importance in explaining the dependent variable, then selected the top-ranked predictor variable to use in the models.

We then selected the most important predictor from pairs of the above grouping of correlated variables. In the case that several variables were intercorrelated, we selected to retain the maximum number of variables that had the strongest relationship with our dependent variable. To compare the relative influence of variables within different groups, we used the hier.part package in R, which provides the relative independent influence of all variables considered.

After selecting the suites of environmental predictor variables, we then generated random sample points distributed across all forested regions of the study area at 1-km spacing (to reduce potential for spatial autocorrelation). At each location of each sample point, we extracted values from the mapped response and explanatory variables to use in the statistical modeling.

We initially explored multiple statistical and machine-learning approaches to determine which was most appropriate for this application. For each modeling methodology, we assessed differences in prediction accuracy and compared how each model ranked the relative importance of the explanatory variables relative to what is known in the literature. Due to its high prediction accuracy and ability to capture variable interactions and nonlinear relationships, we selected the Random Forest approach. Random Forest is a machine learning algorithm that works by developing numerous decision trees and combining results derived from a bootstrapping algorithm that compares models using randomly selected subsets of the explanatory variables.

Random Forest calculates the relative importance of different predictor variables by randomly permuting their values, making predictions using these shuffled values, and comparing the accuracy of permuted models to models using the real values of the variables. The mean decrease in model accuracy that results from permuting the data is recorded and averaged across all trees in the model. Larger decreases in accuracy reflect larger variable importance because the permutation of that variable is highly influential in model results.

We created Random Forest models and prediction maps using the response and explanatory variables described above using the package randomForest in R (https://www.rdocumentation.org/packages/randomForest/versions/4.7-1.1/topics/randomForest). We created models at two scales: across the entire southern Sierra Nevada study area, and within multiple subregions (for each National Park and National Forest in the study area). We summarized results of each model to three analytical spatial units:

270m, 450m, and catchments (catchments represent the direct or local drainage area for an individual stream reach; https://www.usgs.gov/national-hydrography/nhdplus-high-resolution). Results of these analyses informed selection of the best predictors, operators, weights, and interaction effects within EEMS logic models.

Results

Drought Vulnerability

Figure 1 shows modeled drought vulnerability (2015-2017) across the study region using 2014 ground conditions and the predictors in Table 1.

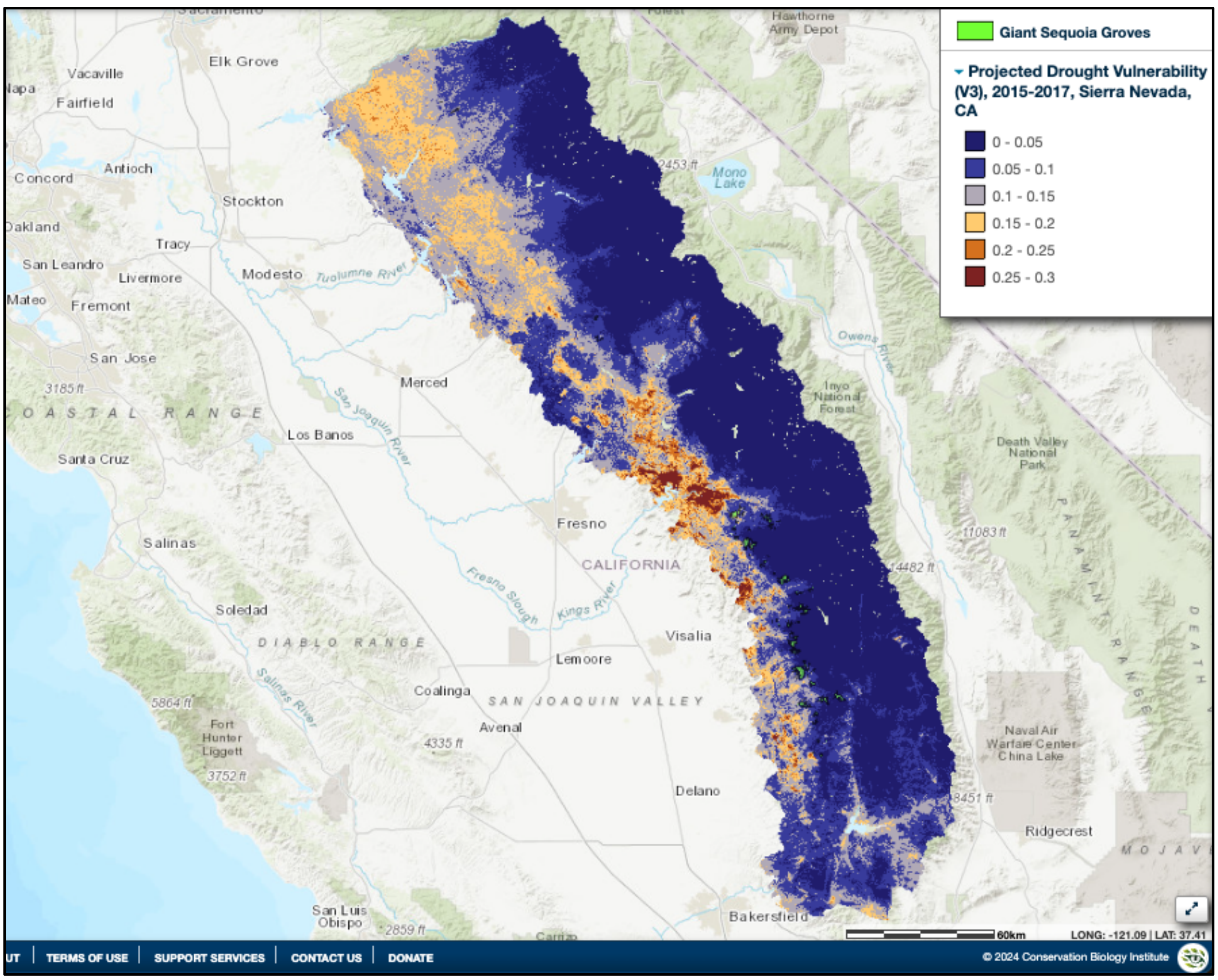

Figure 1. Modeled drought vulnerability (2015-2017) across the study region using 2014 ground conditions.

Table 1. Drought Vulnerability Model Predictors in order of relative importance (mean decrease in model accuracy after permuting the variable).

Predictor	Relative Importance
Mean actual evapotranspiration (AET), 1981-2010	21.7
Maximum vapor pressure deficit, 2014	19.8
Bedrock conductivity	18.4
Mean annual precipitation, 1981-2010	18.0
Percent clay	17.5
Mean annual runoff, 1981-2010	17.0
Structural diversity	16.7
Annual heat-moisture index, 2014	16.6
Mean relative humidity, 1981-2010	16.0
Mean climatic water deficit (CWD), 1981-2010	15.8
Mean summer heat-moisture index, 2012-2014	15.8
Mean precipitation as snow, 2012-2014	15.7
Percent silt	15.6
Mean annual recharge, 1981-2010	15.1
Available water capacity (AWC), 0-25 cm	14.9
Distance to wet meadow	14.2
Normalized differenced vegetation index (NDVI), 2014	13.1
Solar Insolation index	12.6
Soil porosity	12.0
Mean stand height, 2012-2014	11.9
Slope	11.4
Proportion of 500m moving window with 'severely drought vulnerabl	11.0
Mean May - September precipitation, 2012-2014	10.6
Reineke's stand density index, 2014	9.9
Landscape evaporative response index (LERI), 2014	9.2
Average monthly solar radiation	8.1
Tree density, 2014	7.7
Number of times burned, 2014	7.5
Southwest index	5.7
Wetness index	4.8
Number of tree canopy layers present, 2014	4.5

Climate
Soils
Hydrology
Vegetation
Topography
Fire History

Figure 2 shows the same output zoomed in on a portion of the study region to illustrate drought conditions near giant sequoia groves. Note that most groves are outside of areas with high drought vulnerability. These maps can be explored in detail at the following link: [Projected Drought Vulnerability (V3), 2015-2017, Sierra Nevada, CA](#).

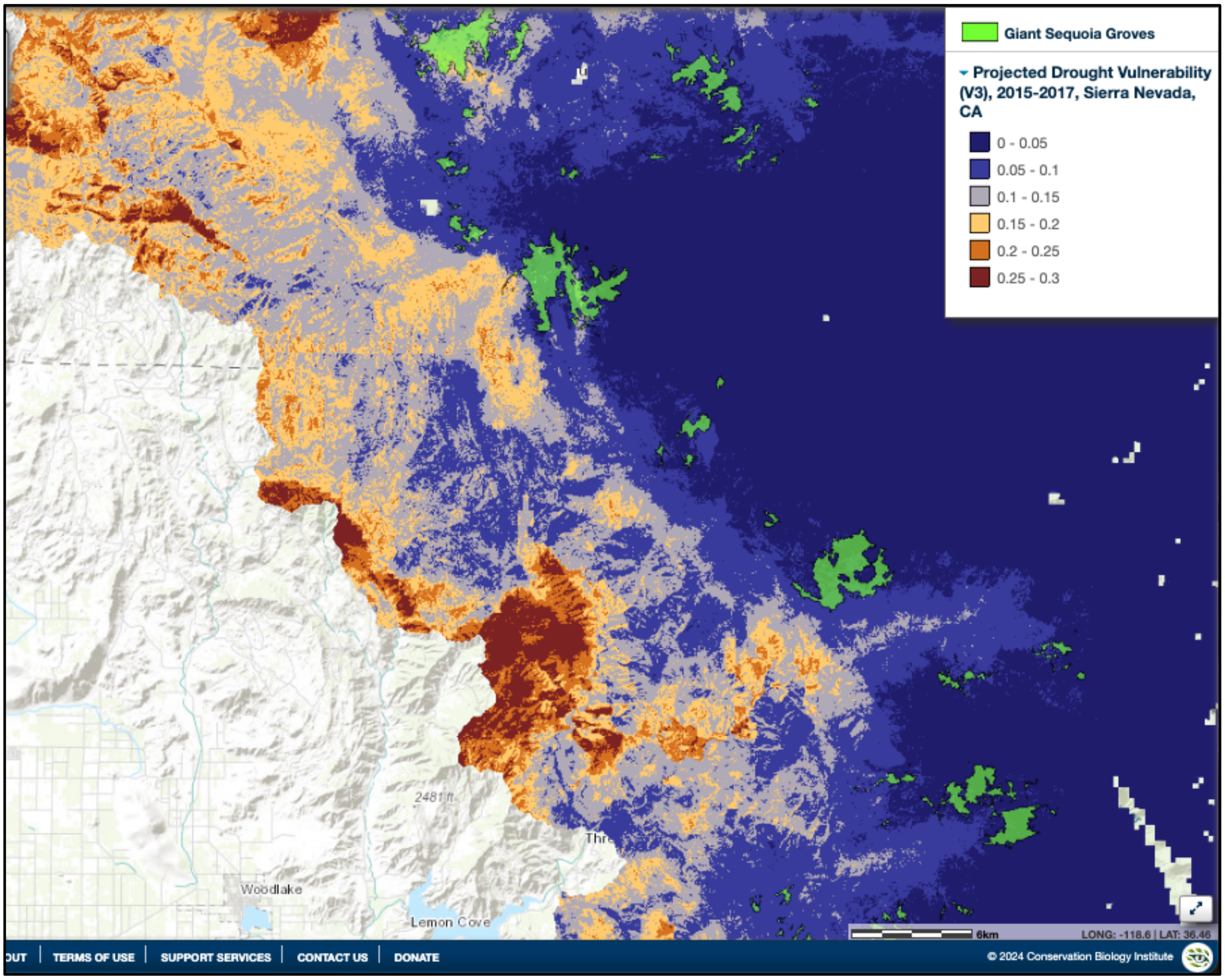

Figure 2. Drought Vulnerability Model zoomed to a portion of the study region showing sequoia groves (green).

Severe Wildfire Risk

Figure 3 shows the results of the severe wildfire risk model (as Composite Burn Index) across the study region using 2017-2022 ground conditions; and Figure 4 shows a portion of the study area, zoomed in to illustrate severe wildfire risk in and near giant sequoia groves. Note that some groves overlap areas modeled to be at high risk of severe wildfire. These maps can be examined in detail at this Data Basin link: **Projected Fire Severity (V9a), 2017-2022, Sierra Nevada, CA**.

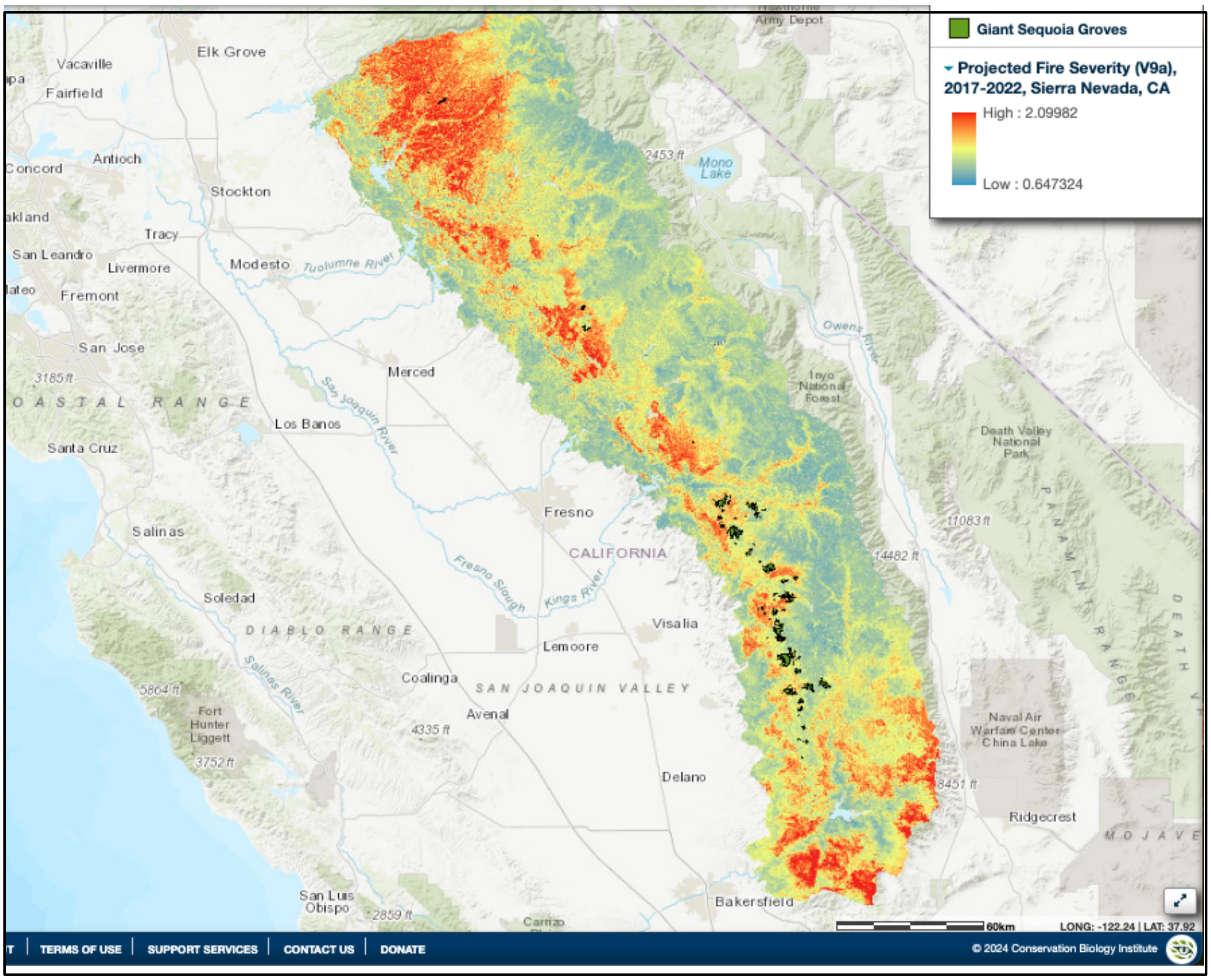

Figure 3. Map output from the severe wildfire risk model, showing giant sequoia groves (black outline).

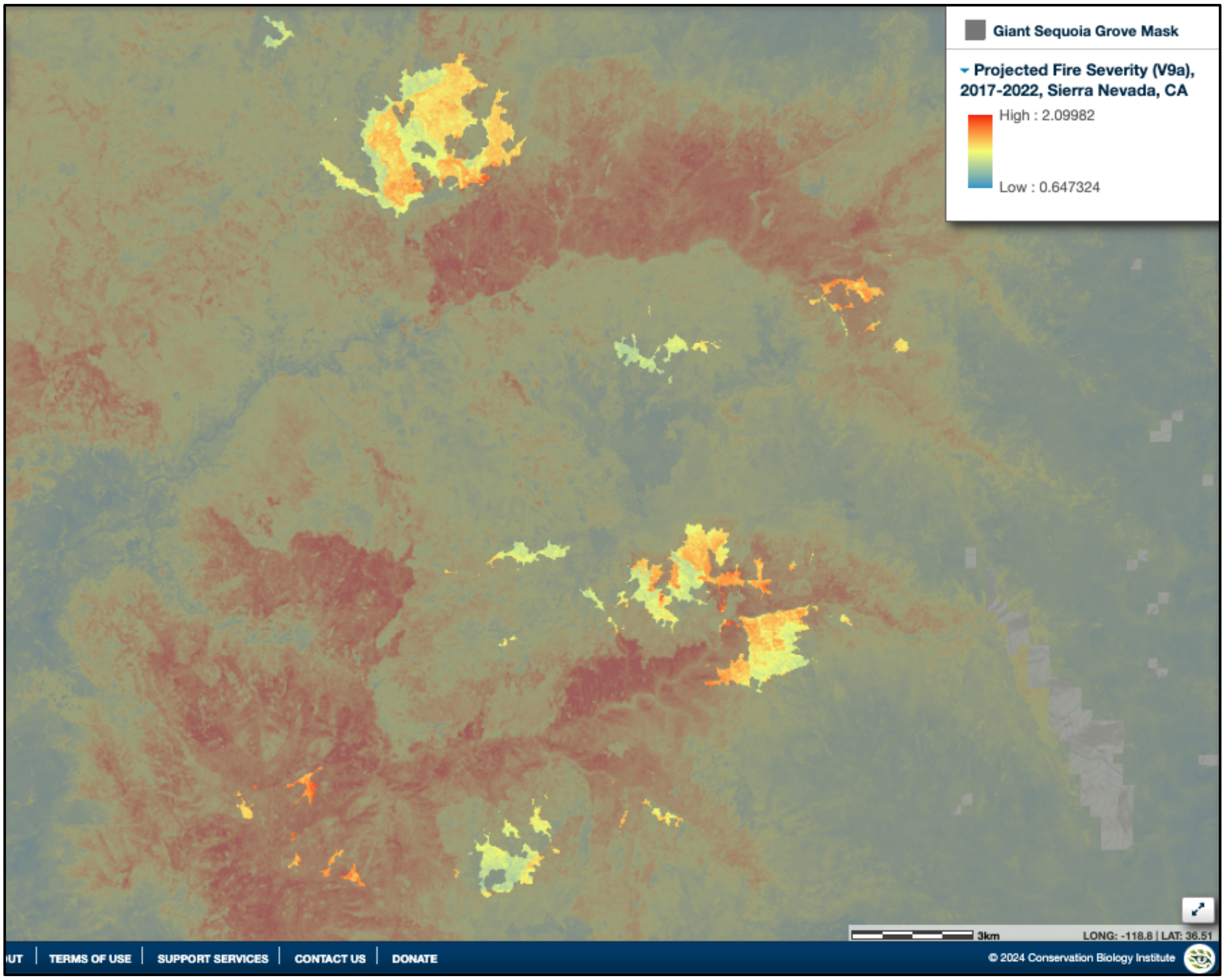

Figure 4. Projected Fire Severity Model output, highlighting several giant sequoia groves.

Table 2. Severe Wildfire Risk Model Predictors in order of relative importance (mean decrease in model accuracy after permuting the data of the variable).

Variable Name	Relative Importance
NDVI (Normalized Differenced Vegetation Index)	58.0
Elevation	44.3
Fire Year Annual Heat Moisture Index	40.4
Fire Year Summer Heat Moisture Index	39.1
Fire Year Mean Temperature Coldest Month	38.4
Five Year Precipitation as Snow	36.5
Maximum Vapor Pressure Deficit, 1991-2020	35.9
Ladder Fuels, year before fire 2017-2020 fires	35.5
Mean Annual Precipitation, 1991-2020	34.8
Time Since Last Fire, year of fire	31.5
Mean Temperature Difference between Warmest & Coldest Month	29.6
Distance to Roads	28.2
Drought-induced Forest Die-off, 5 years before fire	26.8
Mean Annual Relative Humidity, 1991-2020	26.7
Wind Exposure Index	26.3
Mean Climatic Water Deficit, 1991-2020	25.8
Mean Climatic Water Deficit, year of fire	25.2
Distance to Development	24.7
Canopy Bulk Density, year before fire	24.6
Topographic Dissection Index	24.1
Reineke's Stand Density Index, year before fire	22.7
Soil Thickness	22.2
Slope	20.8
Soil Porosity	20.6
Topographic Wetness Index	16.6
Structural Diversity (based on different dbh classes)	16.3
Canopy Base Height, year before fire	16.2
Drought-induced Mortality, 1 yr before fire	14.7
Insolation Index	14.3
Number of Times Burned over last 20 years	12.7
Number of Tree Canopy Layers, year before fire	12.3

Climate
Soils
Hydrology
Vegetation
Topography
Fire History
Development

EEMS Models

EEMS models (Sheehan and Gough 2016) are at the core of the decision-support system. This tree-based fuzzy-logic modeling approach allows the combination of any spatial data set, from raw input data to statistical model results to expert opinion. They are modular, allowing users to swap in new or better data sets and model inputs as they become available; they are totally transparent, allowing users to understand exactly how various inputs and interactions affect outputs; they are flexible, allowing users to modify variable operators or weights to explore ramifications; and they provide users with clear and useful maps of every component.

EEMS fuzzy-logic models are hierarchical (tree-based) — that is, data flows from the bottom up in order to answer a primary question at the top of the hierarchy. Each map-based node (box) in the hierarchy represents a proposition, which is simply a statement that can either be totally true (+1), totally false (-1), or somewhere in-between at any given location. Starting at the bottom of the hierarchy, data layers are combined to create a series of fuzzy truth propositions using a number of available fuzzy-logic operators (e.g., OR, AND, UNION) with each logic outcome assigned to the node immediately above it. In addition to logic operators, the model is controlled by assigning meaningful individual thresholds and weighting of each input and intermediate node.

Methods

We developed EEMS decision-support models and maps for forest resilience factors at two grid resolutions: 90m for covering the entire study area, and 30m for finer-scale assessment within each of six major management areas of interest:

- Stanislaus National Forest
- Sierra National Forest
- Sequoia National Forest
- Yosemite National Park
- Sequoia & Kings Canyon National Parks
- Sequoia Grove Priority Management Area

Each model was developed iteratively based on the literature, results of statistical analyses and models, and expert opinion. Alternative draft EEMS models were created for comparison and subjected to multiple review cycles. This included comparing maps of tree mortality patterns, severe wildfire, and other pertinent data layers to individual variables and EEMS logic layers to visually evaluate model fits to expectations. Based on these iterative analyses, draft EEMS models were posted on EEMS Online and evaluated by science team members and other stakeholders. Final results were then loaded to the CBI data catalog and Data Basin, as well as EEMS Online.

Figure 5. Conceptual diagram of the relationships between multiple threats to forest resilience (drought, insect, and fire influences) showing how outputs from one model (e.g., drought stress) represent inputs in other models (e.g., fire or insect risk).

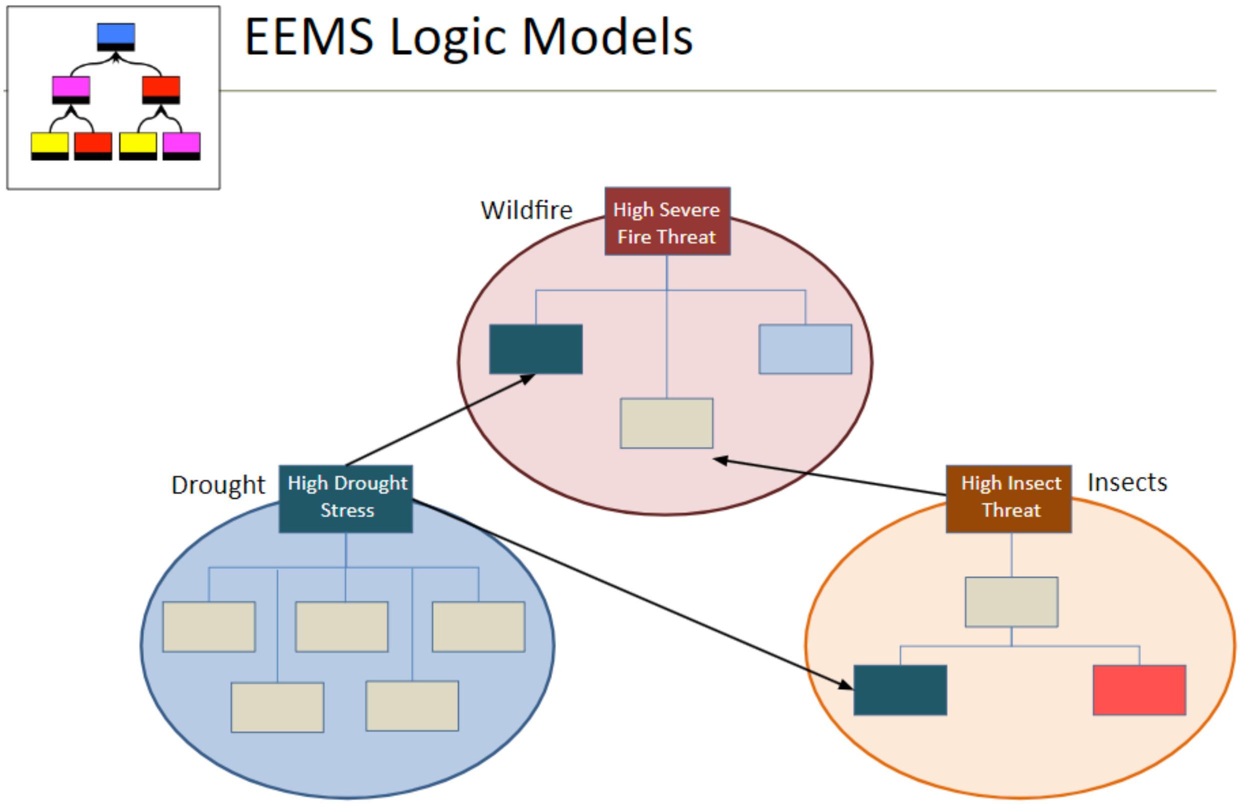

Figure 5. Conceptual model of how various types of stressors may interact on the landscape and therefore how EEMS models for each stressor may relate to one another.

In practice, although this conceptual framework has value, it proved difficult to implement with available data and knowledge. After drafting, reviewing, and refining myriad possible EEMS models for drought, insect, and fire stress (or conversely, resilience) we carried forward the following EEMS models for use in the decision-support system: Drought Stress and Wildfire Fuels Model, which are described below.

Results

Drought Stress Models

A Drought Stress EEMS model was developed to help guide where vegetation management may increase forest resilience by reducing competition amongst trees and shrubs for available groundwater. The logic behind this model (Figure 6) is that Mediterranean forests are limited by water availability to individual trees and shrubs within a forest stand, and that these trees and shrubs compete with one another for available water. As vegetation becomes increasingly dense, competition increases and eventually leads to stress, self-thinning, and mortality of individual trees and shrubs. Relative stand density index is a strong predictor of the degree of competition and stress (North et al. 2022) in concert with total above-ground live tree carbon or biomass.

Water availability is represented in the model using variables summarized in Table 3, including Climatic Water Deficit (CWD) as defined by Stephenson (1998), a Topographic Wetness Index (which indicates the amount of surface or groundwater likely to collect due to topographic position), and the amount of solar radiation hitting the ground surface (Heatload). Competition is represented in the model using Stand Density Index (SDI) and Above Ground Live Tree Carbon data from the Sierra Nevada Regional Resource Kit.

The model can be explored using EEMS Online at this link: **Drought Stress Version 2**.

Table 3: Data used in the Drought Stress EEMS Models.

Model Input	Dataset	Source	Link
Topographic Wetness Index	Topographic Wetness Index, Sierra Nevada	*Heather Rustigian-Romsos, CBI*	Topographic Wetness Index, Sierra Nevada
Heatload	Western US 30m Raw Heatload Values	*USGS*	Western US 30m Raw Heatload Values | USGS Science Data Catalog
Above Ground Live Tree Carbon	Aboveground Live Tree Carbon	*Sierra Nevada Regional Resource Kit*	Sierra Nevada Regional Resource Kit
Stand Density Index	SDI: Stand Density Index Zeide 1983	*Sierra Nevada Regional Resource Kit*	Sierra Nevada Regional Resource Kit
Climatic Water Deficit	Climatic Water Deficit, Central Sierra Nevada California, PCM A2 Scenario 2010-2039	*Basin Characterization Model*	2014 California BCM (Basin Characterization Model) Downscaled Climate and Hydrology - 30-year Summaries

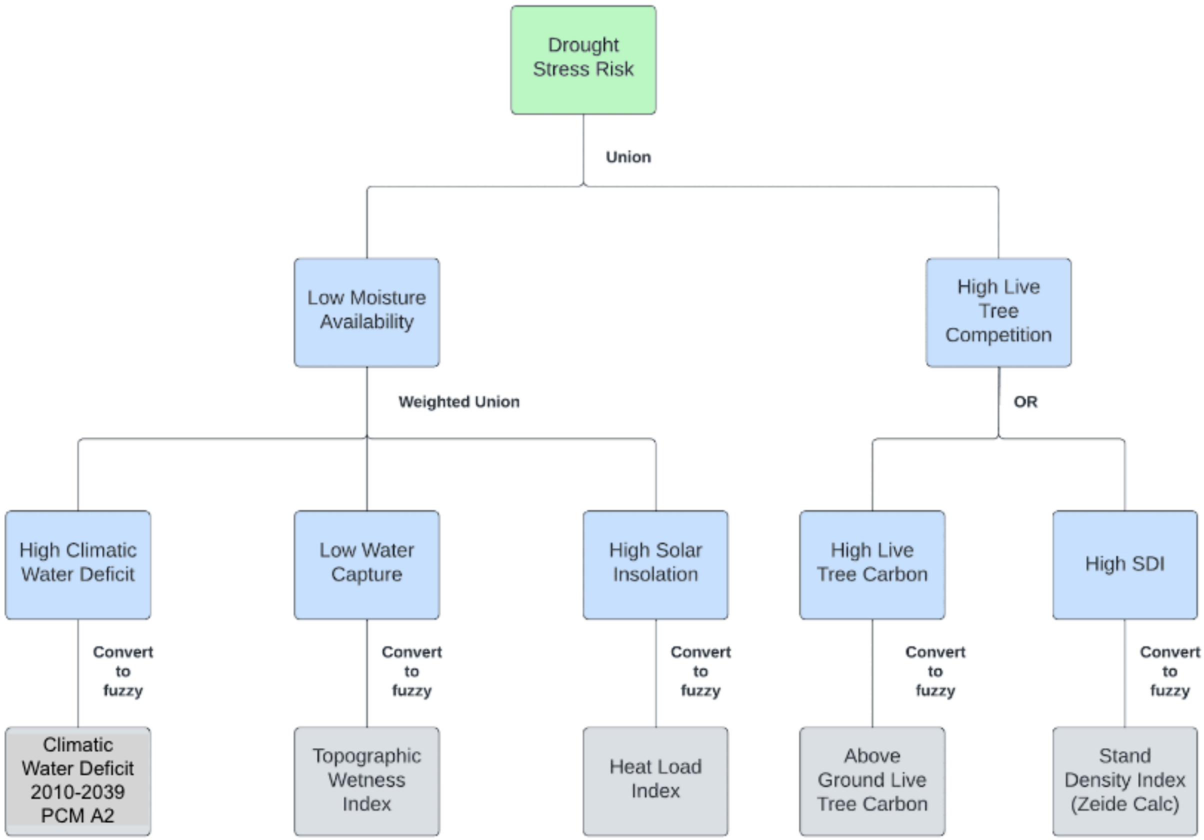

Figure 6: Drought Stress EEMS Model structure (gray = data inputs; blue = intermediate nodes; green = final model result).

Wildfire Fuels Model

This EEMS model was developed to help guide where managers may wish to prioritize where reducing forest fuels is most needed. Spatial datasets used in this model relied heavily on the most recent Sierra Nevada Regional Resource Kit (https://wildfiretaskforce.org/sierra-nevada-regional-resource-kit/). The datasets selected for inclusion (Table 4) were based primarily on those characteristics that contribute significantly to remotely sensed Normalized Difference Vegetation Index (NDVI). The relative statistical importance of these factors (Table 5) also helped guide weightings in the overall model.

Table 4. Data used in the Wildfire Fuels EEMS Models.

Dataset Name	Source
Proportion of Maximum Stand Density Index (Zeide Calculations)	Sierra Nevada Regional Resource Kit
Snag Density (20-29.9" dbh)	Sierra Nevada Regional Resource Kit
Snag Density (30-39.9" dbh)	Sierra Nevada Regional Resource Kit
Snag Density (>40" dbh)	Sierra Nevada Regional Resource Kit
Tree to Shrub Ratio	Sierra Nevada Regional Resource Kit
Standing Dead and Ladder Fuels (Short tons/acre)	Sierra Nevada Regional Resource Kit
Total Dead/Down Fuels (Short tons/acre)	Sierra Nevada Regional Resource Kit
Canopy Cover (%)	California Forest Observatory SALO Sciences
Canopy Height (m)	California Forest Observatory SALO Sciences

Table 5. Relative contribution of forest condition factors to Normalized Difference Vegetation Index (NDVI).

Forest Characteristic	Contribution
Stand Density Index (LEMMA GNN)	40.9
Ladder Fuels (Salo Sciences CFO)	27.2
Canopy Cover (LEMMA GNN)	18.9
Canopy Bulk Density (Salo Sciences CFO)	5.3
Drought-induced Mortality, 5 years before fire (Wang 2021)	3.4

The model diagram for Wildfire Fuels (Figure 7) shows the hierarchical arrangement of the spatial data inputs (in gray), intermediate nodes (in blue), and the final result map (in green). All logic operators used are displayed between each node or series of nodes. The transition between raw input data and relativized along the true/false continuum for the model used one of two commands. The Convert to fuzzy command was the most common and assigns a simple true/false continuum for a range of values. The Convert to fuzzy curve command is a bit more complex as it assigns a curve based on the range of values for each input layer. Canopy Height used the Convert to fuzzy curve command assigning the highest truth value to tree heights between 10m and 14m as these stands are more susceptible to more severe fires as opposed to larger trees (Miller et al. 2012) (Figure 8A). The same command was used in setting thresholds for the Shrub Fuels component with the maximum truth value assigned to any tree to shrub ratio of 10 or below (excluding zero) and -1 at 50 or above (Figure 8B).

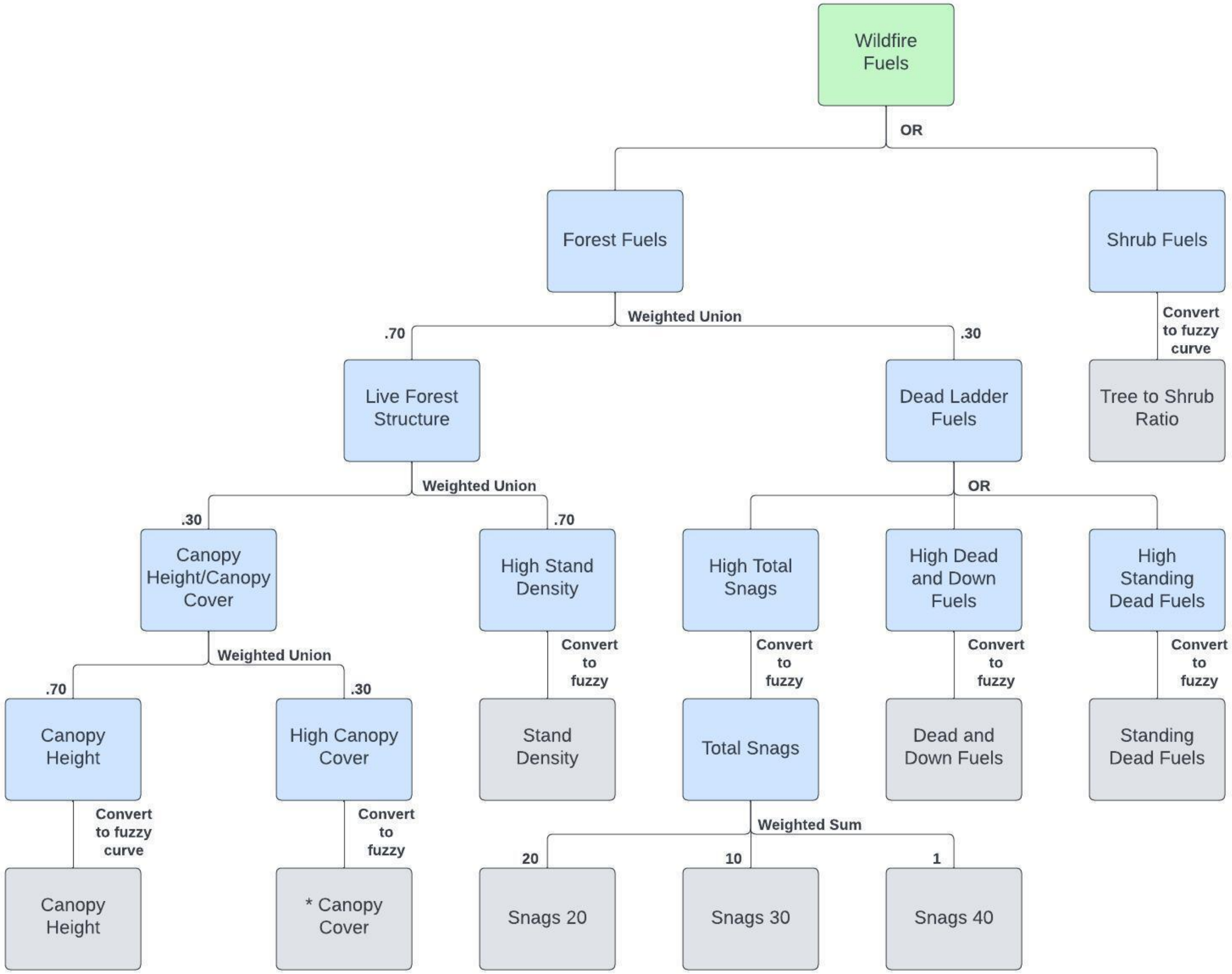

Figure 7. Wildfire Fuels EEMS Model structure (gray = data inputs; blue = intermediate nodes; green = final model result).

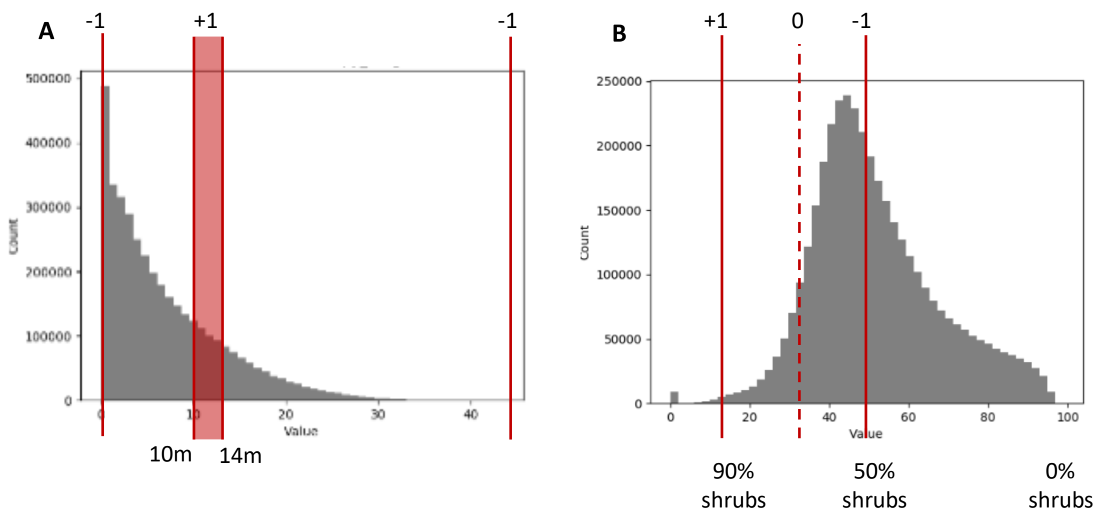

Figure 8. Convert to fuzzy curve histograms for assigning threshold values for Canopy Height (A) and Tree to Shrub Ratio (B).

Working from the top of the diagram down, Wildfire Fuels was created using an OR logic operator between Forest Fuels and Shrub Fuels, meaning the higher of the two intermediate maps for each grid cell was selected for the final result map. Forest Fuels included nine different input datasets – five to create a Dead Ladder Fuels node and three to create a Live Forest Structure node. The Forest Fuels node was created using a Weighted Union logic operator with 70 percent of the influence from the Live Forest Structure branch and 30 percent from the Dead Ladder Fuels branch.

The Dead Ladder Fuels node was created by combining High Standing Dead Fuels, High Dead and Down Fuels, and High Total Snags using an OR operator. High Total Snags intermediate node was created by using a Weighted Sum operator to add the various size snags in a weighted fashion for each grid cell. The smallest dimension snags (20-inch dbh) were assigned the highest weight of 20, followed by the next side category (30-inch dbh) with a weight of 10, and finally 40-inch dbh snags were assigned a weight of 1.

Influenced by the NDVI statistical results shown in Table 6, the Live Forest Structure node was created using a Weighted Union operator with 70 percent contributed by High Stand Density and 30 percent by the Canopy Height/Canopy Cover node. The Canopy Height/Canopy Cover node was a bit more complex primarily due to the Canopy Cover data, which had to be modified using the Canopy Height data (all grid cells with trees ≤3 meters) before serving as the Canopy Cover input layer in the model. As previously reported, the “truest” canopy height range was between 10m and 14m.

The 90m resolution results for the entire study area (Figure 9) shows the distribution of wildfire fuels based on vegetation conditions at the time the input data was generated. Of the nearly 7.5 million acres of the study area, over one-third contains either very high or high wildfire fuel conditions based on the modeling results (Table 6).

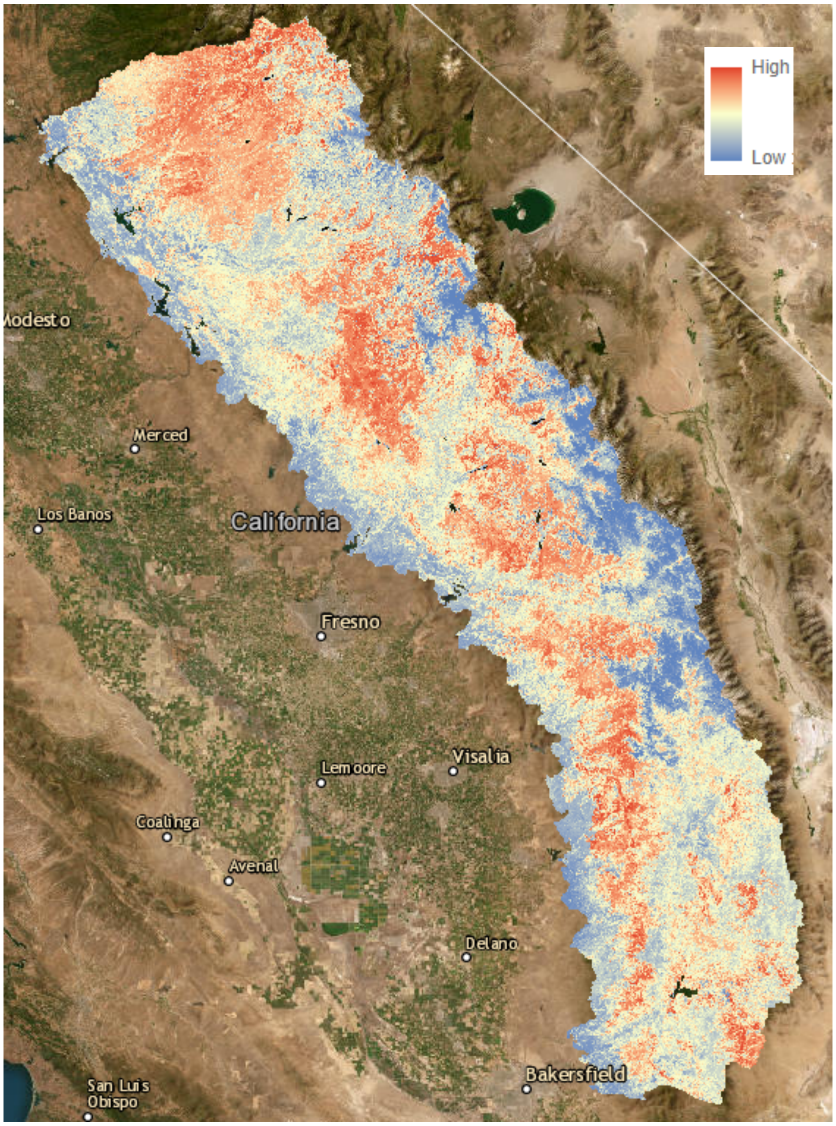

Figure 9. Map of Wildfire Fuels based on the 90m resolution EEMS model for the entire southern Sierra Nevada study area.

Table 6. Summary results from the 90m EEMS Wildfire Fuels model for the entire southern Sierra Nevada study area. Continuous EEMS values were classified into five equal interval classes from very high to very low.

Classes	Area (ac)	Percent
Very High	1,310,915	17%
High	1,583,440	21%
Medium	1,907,726	25%
Low	1,747,119	23%
Very Low	947,059	13%
Totals	7,496,259	100%

The 30m EEMS Wildfire Fuels model runs for each of the major management areas provided a more detailed assessment of fuel conditions in each of the distinct landscapes that yielded varied fuel condition profiles. It is important to note that each of subregional EEMS models operated within the range of input values encountered in that particular subset in order to more accurately identify areas within each subregion that contain potentially dangerous fuel conditions.

Based on the combined 30m EEMS subregional Wildfire Fuels model results, which included 5.2 million acres of the nearly 7.5 million acres of the entire southern Sierra Nevada study area[1], around 2 million acres were found to contain very high or high fuel loads. Nearly half (959,733 acres) of these combined classes were found in the Stanislaus and Sierra national forests (Table 7). Each management area contained significant levels of very high or high fuel load classes. Sequoia NF and Sequoia-Kings Canyon NP model results showed the least percentage of high fuel classes largely due to the large portion of high elevation alpine areas.

The companion maps and online links for the 30m EEMS subregional model results summarized in the previous table show the spatial distribution of the various wildfire fuel classes. These maps can be explored at the following Data Basin links:

- Wildfire Fuels: Stanislaus National Forest
- Wildfire Fuels: Sierra National Forest
- Wildfire Fuels: Sequoia National Forest
- Wildfire Fuels: Yosemite National Park
- Wildfire Fuels: Sequoia-Kings Canyon National Park
- Wildfire Fuels: Sequoia Grove Priority Management Area

[1] Approximately 2.5 million acres of land outside of the chosen land management subregions evaluated included Inyo National Forest, scattered BLM lands and private lands, primarily on the western edge of the full study area.

Table 7. Summary results from the 30m EEMS Wildfire Fuels Model for each of the management subregions in the southern Sierra Nevada study area.

	Stanislaus NF		Sierra NF[2]		Sequoia NF[3]	
Classes	Area (ac)	Percent	Area (ac)	Percent	Area (ac)	Percent
Very High	236,627	21.9%	122,482	22.9%	81,978	10.9%
High	321,804	29.8%	278,820	21.6%	214,339	18.9%
Medium	239,102	22.2%	365,201	26.4%	226,955	26.0%
Low	207,512	19.2%	298,473	20.2%	212,985	30.0%
Very Low	73,934	6.9%	316,348	8.9%	136,450	14.1%
Totals	1,078,979	100.0%	1,381,324	100.0%	872,707	100.0%

	Yosemite NP		Sequoia-Kings NP[4]		Sequoia Grove Priority Management Area[5]	
Classes	Area (ac)	Percent	Area (ac)	Percent	Area (ac)	Percent
Very High	177,330	24.1%	86,274	12.1%	85,331	20.0%
High	134,959	18.4%	94,923	13.3%	129,232	30.2%
Medium	166,022	22.6%	144,020	20.2%	125,182	29.3%
Low	169,132	23.0%	151,893	21.3%	51,098	11.9%
Very Low	87,924	12.0%	236,710	33.2%	36,856	8.6%
Totals	735,367	100.0%	713,820	100.0%	427,699	100.0%

[2] Total area for the Sierra National Forest is reduced by 4,576 acres, which is captured as part of the Sequoia Grove Priority Management Area.

[3] Total area for the Sequoia National Forest is reduced by 259,537 acres, which is captured as part of the Sequoia Grove Priority Management Area.

[4] Total area for the Sequoia-Kings Canyon National Park is reduced by 133,444 acres, which is captured as part of the Sequoia Grove Priority Management Area.

[5] Comprised largely of the area from the three management areas listed above plus an additional 30,142 acres from other marginal areas.

Wind-drag Estimates

We modeled vegetation wind-drag coefficients using CFO forest structure variables. These can be combined with terrain effects on air flow to map landscape wind-drag coefficients (10m horizontal, 1m vertical resolution), which in turn can be used to map where atmospheric coupling is most likely to drive extreme wildfire behavior under varying wind speeds. Fire-atmosphere coupling is most likely to occur where the ratio of fire-induced winds approaches or exceeds prevailing winds. Maps flagging locations where future megafires are most likely to occur would be a valuable contribution to planning forest management interventions.

Methods

After investigating opportunities to use Bayesian hierarchical modeling with existing data sources, our modeling approach changed. We instead took a more direct, physics-based approach to calculating wind fields as a function of vegetation structure using CFO forest structure data and wind-tunnel estimates of drag through various types of tree and shrub canopies. These results can be applied to improving assessment of the effects and effectiveness of fuels treatments using operational fire models, which to date have not accounted for how reducing fuels also increases ventilation (e.g., FlamMap 6.2). Although the scientific consensus has been that fuels treatments reduce fire intensity within a treatment footprint, it is essential to also understand and quantify how they may also increase ventilation through the area as well as into neighboring, untreated areas, potentially increasing fire intensity in ways not predicted by existing models.

Specifically, we calculated and mapped wind-drag coefficients at 10m horizontal and 1m vertical resolution based on how vegetation affects air flow through, below, within, and above forest canopies. This was done by mathematically inverting Lidar-based CFO forest structure variables (canopy height, canopy base height, canopy cover, etc.) to create a 3D approximation of forest structure in terms of the number of trees and shrubs of varying heights and shapes on the landscape. The direct effects of foliage on air flow through tree and shrub canopies were estimated based on wind-tunnel experiments performed by the National Institute of Standards and Technology (Falkenstein-Smith et al. 2019). Fluid dynamic equations were used to estimate the resulting vegetation-based wind fields, or how oxygen flow is affected by vegetation structure.

Results

Vegetation wind drag results are gathered into a Data Basin gallery here - **Vegetation Wind Drag Coefficients for the Southern Sierra Nevada.** They are presented in 1m height increments from ground level to 10 m above ground, and summarized as 5m averages from 0-5 m above ground to 25-30 m above ground. Figure 10 illustrates wind drag coefficients (kappa) for 0-5 m above ground for a portion of the study area.

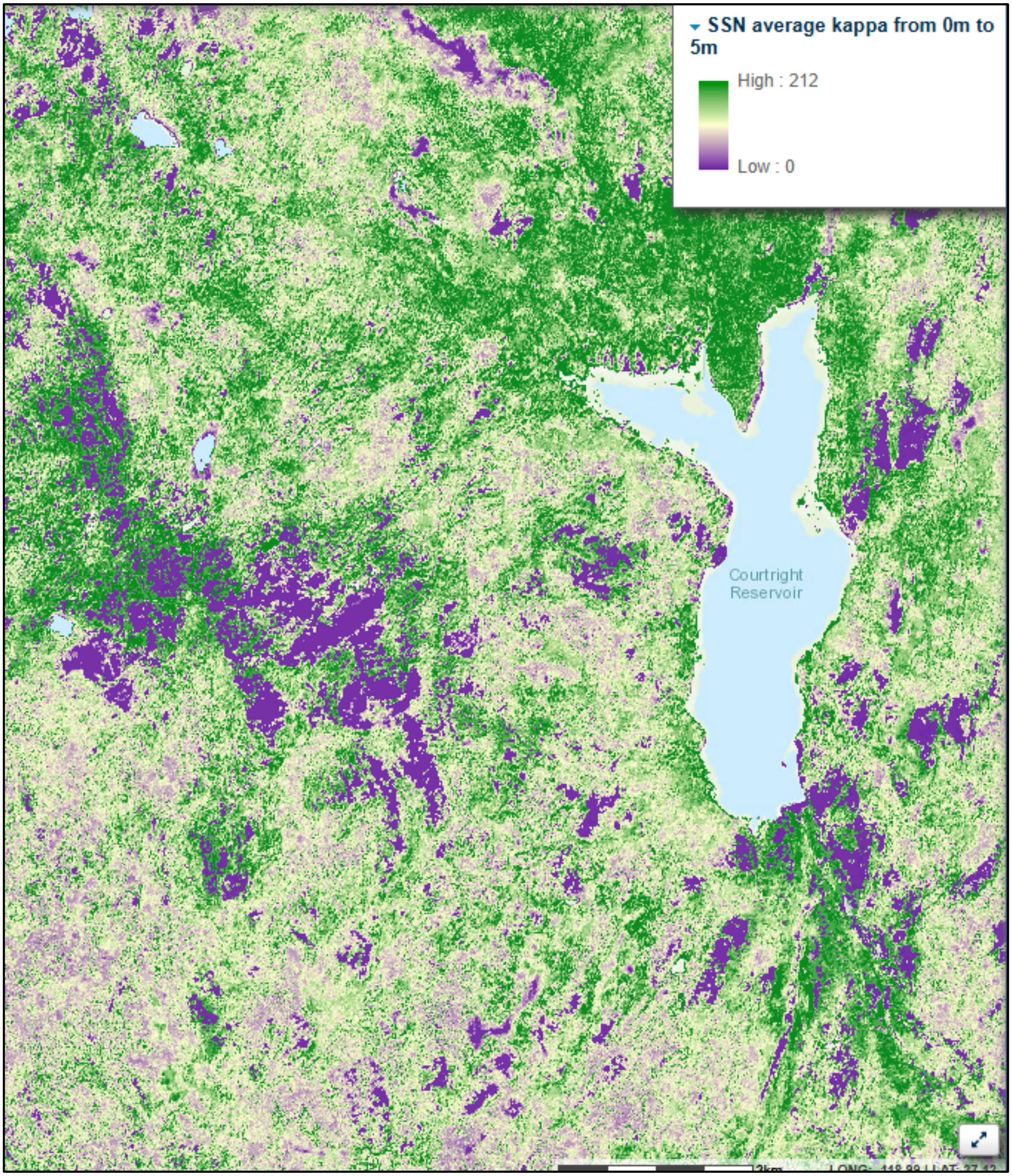

Figure 10. Example output of vegetation wind-drag coefficients (kappa) averaged over 0-5 m above ground for a portion of the study area. Darker green areas have greatly reduced air flow near the ground due to dense vegetation below 5 m height.

These results can be applied to improving assessment of the effects and effectiveness of fuels treatments using operational fire models, which to date have not accounted for how reducing fuels also increases ventilation (e.g., FlamMap 6.2). They can also be coupled with terrain effects on winds to identify places on the landscape where together vegetation and terrain effects on winds may increase risks of extreme fire behavior, for example where forest thinning has potential to actually increase air flow in risky locations during fire, including chances of fire-atmosphere coupling.

Forest Resilience Exploration Maps in Data Basin

CBI created an array of interactive maps in Data Basin to facilitate exploration of all of the model outputs and to support decision-making concerning forest management actions. The maps combine results of statistical models with EEMS models and other pertinent GIS layers, such as boundaries of management areas and giant sequoia groves.

Southern Sierra Region-Wide Maps

The following map covers the entire southern Sierra Nevada planning area at 90m resolution:

Southern Sierra Nevada Regional Results
https://databasin.org/maps/2765b2e62d3f440f89c9e7d601f854a8/

Management Area Maps

In addition, we prepared the following maps at finer 30m resolution for each of the six focused management areas within the larger study region (individual national forests and parks and the Sequoia groves management priority area). These provide resource managers in each area to explore in more detail conditions under their jurisdictions:

Stanislaus National Forest
https://databasin.org/maps/6b5b33f5701e4bbc82024442c20578fc/

Sierra National Forest
https://databasin.org/maps/3cc4b954292b4dbeb9be738f7c3be196/

Sequoia National Forest
https://databasin.org/maps/77f9ecf2c2dd49e0b9bb94e9b3e4d437/

Sequoia Kings Canyon National Park
https://databasin.org/maps/76cb692c817b414586cf808414dff2a1/

Yosemite National Park
https://databasin.org/maps/19045f5d798342dab6876988595c7cfb/

Sequoia Management Priority Area
https://databasin.org/maps/bf29e919d04c48b4831650b6a2fca459/

Stakeholder Outreach

Workshops and smaller-group meetings were held with the project's stakeholder partners to understand their need for decision support, gain access to important knowledge and data, and co-develop the models and DSS. During the process, the original "Sequoia Regional Partnership" was replaced by a largely overlapping group of partners organized as the "Giant Sequoia Lands Coalition." This new coalition is carrying our products over into a new data portal and decision-support dashboard, which they are using to plan forest management actions, as described in more detail below.

Sequoia Regional Partnership

Early in our collaboration, we referred to the group of southern Sierra Nevada forest and giant sequoia lands managers with whom we were collaborating as the "Sequoia Regional Partnership." The core group consisted of representatives from the US Forest Service, National Parks Service, US Geological Survey, Great Basin Institute, American Forests, Sierra Nevada Conservancy, and Save the Redwoods League (Table 8). These members brought in their specialists in data availability, research, and GIS analysis to support the process. In 2021 CBI and the Sequoia Regional Partnership launched this effort with seed funding from Sequoia-Kings Canyon National Park and Save the Redwoods League. Later we jointly applied for and were awarded this CAL FIRE Forest Health Research Grant.

Giant Sequoia Lands Coalition

During 2022 and 2023, as a result of catastrophic fires that killed a large number of giant sequoias, these forest management organizations became more coordinated under the title of the "Giant Sequoia Lands Coalition" (GSLC, see https://giantsequoias.org/), and began working on a Range-wide Giant Sequoia Health and Resilience Assessment and 5-year Strategy to prioritize and plan fuels-reduction and restoration treatments in the more than 100 groves of giant sequoias across all land ownerships. CBI was included in the GSLC's project funded by the Sierra Nevada Conservancy to create a Giant Sequoia Data Portal and to gather and analyze data to support the Assessment and 5-year Strategy. Consequently our efforts at CBI shifted to take guidance from and directly support the GSLC.

Table 8. Core Members of the Project Stakeholder Group.

Name	Email Address	Affiliation
Marianne Emmendorfer	<marianne.emmendorfer@usda.gov>	US Forest Service
Gretchen Fitzgerald	<gretchen.fitzgerald2@usda.gov>	US Forest Service
Sarah Sawyer	sarah.sawyer@usda.gov	NPS, National Wildlife Ecologist
Christina Liang	christina.liang@usda.gov	NPS R5 Ecosystem Mgt. Wildlife Ecologist
Marc Meyer	<marc.meyer@usda.gov>	US Forest Service
Angel Prieto	Angel Prieto <angel.prieto@usda.gov>	US Forest Service
Amarina Wuenschel	amarina.e.wuenschel@usda.gov	Seq/Inyo NF
Chris Sanders	Christopher.Sanders@usda.gov	Seq/NF
Wendy Rannals	wendy.rannals@usda.gov	GIS person for Seq NF
Craig Thompson	craig.thompson@consbio.org	USFS, CBI
Devin Murphy	<dmurphy@thegreatbasininstitute.org>	Great Basin Institute
Sarah Campe	sarah.campe@sierranevada.ca.gov	Sierra Nevada Conservancy
Jean Brennan	ejeanbrennan@gmail.com	Science Coordinator, Giant Sequoia Lands Coalition
Joanna Nelson	jnelson@savetheredwoods.org	Director of Science, Save The Redwoods League
Linnea Harlund	<lhardlund@savetheredwoods.org>	Save The Redwoods League
Timothy Borden	tborden@savetheredwoods.org	Save The Redwoods League
Linnea Harlund	Sarah.Campe@sierranevada.ca.gov	SRL
Christy Brigham	<Christy_Brigham@nps.gov>	SEKI National Park
Andrew Cremers	<Andrew_cremers@nps.gov>	NPS
Joshua James	<joshua_james@nps.gov>	NPS
John Ziegler	John Ziegler <john_ziegler@nps.gov>	NPS
Leif Mathiesen	<leif_mathiesen@nps.gov>	NPS
Paul Hardwick	<paul_hardwick@nps.gov>	NPS
Tony Caprio	<tony_caprio@nps.gov>	NPS
Tyler Coleman	t<tyler_coleman@nps.gov>	NPS
Amy Ziegler	Ziegler, Amy E <amy_ziegler@nps.gov>	NPS
Nate Stephenson	<nstephenson@usgs.gov>	USGS

Stakeholder Workshops

CBI hosted a series of stakeholder workshops throughout the process to understand stakeholder concerns, goals, and objectives; evaluate and obtain data sources; and review and comment on interim and final products.

Forest Resilience Project Model Design Workshop #1

Date: Wednesday, January 5, 2022·11:00am – 1:00pm

Workshop Purpose: CBI staff presented the draft Forest Resilience Management Prioritization Model structure developed with Sequoia Regional Partnership input.

Notes: [Meeting Recording]

Attendees:

- Marianne Emmendorfer, USFS
- Gretchen Fitzgerald, USFS
- Sarah Sawyer, NPS
- March Meyer, USFS
- Angel Prieto, USFS
- Wendy Rannals, Sequoia NF
- Craig Thompson, USFS
- Devin Murphy, Great Basin Institute
- Sarah Campe, Sierra Nevada Conservancy
- Jean Brennan, Giant Sequoia Lands Coalition
- Joanna Nelson, Save the Redwoods League
- Linnea Harland, Save the Redwoods League
- Timothy Borden, Save the Redwoods League
- Christy Brigham, SEKI NP, NPS
- Joshua James, NPS
- John Ziegler, NPS
- Paul Hardwick, NPS
- Tony Caprio, NPS
- Tyler Coleman, NPS
- Nate Stephenson, USGS
- Chris Wikle, University of Missouri
- Joe Wern, NorthWest Research Associates
- Alexandra Syphard, CBI
- Wayne Spencer, CBI
- Gladwin Joseph, CBI
- James Strittholt, CBI
- Deanne DiPietro, CBI
- Heather Rustigian-Romsos, CBI

Forest Resilience Model Review Workshop #2

Date: March 15, 2023

Workshop Purpose: Review the statistical fire and drought models and progress on the wind resistance model.

Slide Presentations: Model Review Meeting Slides
Notes: Meeting Recording

Attendees:

- Jean Brennan, GSLC Coordinator
- Christy Brigham, SEKI NP, NPS
- Marianne Emmendorfer, Sequoia N.F.
- Tony Caprio, NPS
- Ben Barry, Sierra Nevada Conservancy
- Sarah Campe, Sierra Nevada Conservancy
- Gretchen Fitzgerald, Sequoia NF
- Amarina Wuenschel, USFS
- Marc Meyer, USFS
- Adrian Das, USGS
- Amy Ziegler, NPS
- Paul Hardwick, NPS
- Brittany Dyer, American Forests
- Preston Alden, Great Basin Institute
- Jerry Keir, Great Basin Institute
- Shikha Acharya, Great Basin Institute
- Joe Wern, NorthWest Research Associates
- Alexandra Syphard, CBI
- Wayne Spencer, CBI
- Gladwin Joseph, CBI
- James Strittholt, CBI
- Deanne DiPietro, CBI
- Heather Rustigian-Romsos, CBI
- Jacob Strittholt, CBI

Forest Resilience Project Model Review Workshop #3

Date: December 12-13, 2023

Workshop Purpose: Review fire, drought, and wind resistance models and discuss management applications of the Sierra Nevada Forest Resilience Decision-Support System.

Slide Presentations: Project Overview Slides, Wind Drag Modeling

Notes: Meeting recordings: Dec 12 Model Review Workshop, Dec 13 Model Review Workshop

Attendees:

- Adrian Das, USGS
- Gianina Martynn, Plumas Corporation
- Hannah Savin, Plumas Corporation
- Juliana Birkoff, Ag Innovations
- Marianne Emmendorfer, USFS
- Paul Hardwick, NPS
- Christy Brigham, NPS
- Michele Slaton, USFS
- Craig Thompson, USFS
- Joanna Nelson, Save the Redwoods League
- Joe Wern, NorthWest Research Associates
- Alexandra Syphard, CBI
- Wayne Spencer, CBI
- Gladwin Joseph, CBI
- James Strittholt, CBI
- Deanne DiPietro, CBI
- Heather Rustigian-Romsos, CBI
- Jacob Strittholt, CBI

The GSLC Data Portal and Grove Resilience Assessment

In 2022 in response to the impacts of severe drought and catastrophic wildfires in the Southern Sierra Nevada, the Giant Sequoia Lands Coalition (GSLC, https://giantsequoias.org/) began work on a Giant Sequoia Health and Resilience Assessment and 5-Year Grove Management Strategy. This effort will coordinate and prioritize fuels-reduction and restoration treatments on giant sequoia groves across all jurisdictions. Under a grant from the Sierra Nevada Conservancy, the GSLC partnered with Plumas Corporation and CBI to co-create tools and maps needed for these goals, and to create the GSLC Data Portal (https://gslc.databasin.org/, the password is currently “draft”, and after March 2025 will change to “SEGI”). The GSLC Data Portal consequently became the focal decision-support tool for this project, with the maps and models from this effort integrated within it for use by the GSLC.

The GSLC Data Portal, built on CBI’s interactive mapping and data sharing platform Data Basin (databasin.org), supports the Coalition in sharing and applying recent science, collaboratively developing data, and facilitating range-wide grove management decisions. Figure 11 is a screenshot of the GSLC Data Portal at the time of this writing. The GSLC Data Portal was presented at the GSLC’s Annual Meetings in March 2024 and again recently in March 2025. A redesign of the homepage is currently underway to better reflect the needs of the Coalition.

In 2024 CBI worked with the GSLC to develop a method for assessing grove health across the species range. The data produced by this project are providing metrics for forest-scale drought stress and wildfire risk surrounding the giant sequoia groves. These data are being used together with grove-specific information to rank the groves for their vulnerability to these stressors and produce a Prioritized Project Work plan for coordinated treatment and restoration work in 2025 and beyond.

Figure 11. The Giant Sequoia Lands Coalition Data Portal as of March 21, 2025.

Deliverables by Task

Task 1 - Build, Test, and Tune Southern Sierra Nevada Forest Resilience Model

1.1 Inventory of relevant knowledge resources

- **Relevant Knowledge Resources for the Forest Resilience Model: Publications** https://docs.google.com/document/d/18ddb947M3lpezDqS5XYu_5lEioAGqGUUeuja8eJF5GE/edit#heading=h.rsrt4kc1sxqw and Sierra Nevada Forest Resilience PaperPile library with 110 publications relevant to the project - https://paperpile.com/app/shared/eXO0kB

- **Relevant Knowledge Resources for the Sierra Nevada Resilience Project - Data and Models** https://docs.google.com/spreadsheets/d/1P8sCEClrymtqqQx95_gtqh2QNAVzrN7236UMk1n8ZCQ/edit#gid=1815928418. 44 resources are listed; these were reviewed for relevance to the project.

1.2 Forest Resilience Model

Statistical Models:

- **Projected Fire Severity (V9a, Classes), 2017-2022, Sierra Nevada, CA**

  https://databasin.org/datasets/7483da2cfba7416c8fc36d8415ba2587/

- **Projected Drought Vulnerability (V3), 2023, Sierra Nevada, CA**

  https://databasin.org/datasets/58a53278e8dc461e8353c498c08377d2/

EEMS Models:

- **Drought Stress Models**

  Historic time frame (1951-1980): http://eemsonline.org?model=qYC1Klby04UdtaAF3mfhQggslA5QwoL2

  2020-2039 timeframe: http://eemsonline.org?model=52hpLslphwRx2312YwClmBG1y8hXxe37

- **Wildfire Fuels Model**

  https://databasin.org/datasets/6fc3cf3b8d68462e86f8d5e3a5056f3b/

Wind-Drag Models

- https://databasin.org/galleries/171f745a036c4af0b5343dcff27394cc/

Task 2 - Customize DSS for Sequoia Regional Partnership Management Planning Area

2.1 Customized DSS prototype

- **The GSLC Data Portal** is available at http://gslc.databasin.org (password=draft or SEGI)

- **Forest Resilience Exploration Map in Data Basin, Southern Sierra Nevada, California**

  https://databasin.org/maps/e78b5f4ddddf45b2b739ee3a1a2418b1/

- **Southern Sierra Nevada Regional Model Exploration Map in Data Basin**

  https://databasin.org/maps/2765b2e62d3f440f89c9e7d601f854a8/

- **Model Exploration Maps by Management Area**

  Southern Sierra Nevada Forest Resilience Results for the Sequoia National Forest
  https://databasin.org/maps/77f9ecf2c2dd49e0b9bb94e9b3e4d437/

  Southern Sierra Nevada Forest Resilience Results for the Sequoia Kings Canyon National Park
  https://databasin.org/maps/76cb692c817b414586cf808414dff2a1/

  Southern Sierra Nevada Forest Resilience Results for the Yosemite National Park
  https://databasin.org/maps/19045f5d798342dab6876988595c7cfb/

  Southern Sierra Nevada Forest Resilience Results for the Sequoia Management Priority Area
  https://databasin.org/maps/bf29e919d04c48b4831650b6a2fca459/

  Southern Sierra Nevada Forest Resilience Results for the Sierra National Forest
  https://databasin.org/maps/3cc4b954292b4dbeb9be738f7c3be196/

  Southern Sierra Nevada Forest Resilience Results for the Stanislaus National Forest
  https://databasin.org/maps/6b5b33f5701e4bbc82024442c20578fc/

2.2 Online documentation

- Online documentation for the EEMS Online Decision Support System is found at https://eemsonline.org/ on the "About" tab.
- Documentation about the GSLC Data Portal is available in the About the GSLC Data Portal section of the site at http://gslc.databasin.org (password=draft or SEGI)
- Documentation about Data Basin is available at http://databasin.org.

Appendices

A. Relevant Knowledge Resources for the Sierra Nevada Resilience Project - Publications

B. Relevant Knowledge Resources for the Sierra Nevada Resilience Project - Data and Models

C. Correction of California Forest Observatory Forest Structure Metrics for Wind-drag Calculations

D. Statistical Modeling Data Sources

E. EEMS Model Data Sources

References Cited

California Forest Observatory. 2020. A Statewide Tree-Level Forest Monitoring System. Salo Sciences, Inc. San Francisco, CA.

Coen, J. 2018. Some Requirements for Simulating Wildland Fire Behavior Using Insight from Coupled Weather—Wildland Fire Models.

Coen, J. L., W. Schroeder, S. Conway, and L. Tarnay. 2020. Computational modeling of extreme wildland fire events: A synthesis of scientific understanding with applications to forecasting, land management, and firefighter safety. Journal of computational science 45:101152.

Coen, J. L., E. N. Stavros, and J. A. Fites-Kaufman. 2018. Deconstructing the king megafire. Ecological applications: a publication of the Ecological Society of America 28:1565–1580.

Falkenstein-Smith, R., K. McGrattan, B. Toman, and M. Fernandez. 2019. Measurement of the flow resistance of vegetation. National Institute of Standards and Technology, Gaithersburg, MD.

Miller, J. D., C. N. Skinner, H. D. Safford, E. E. Knapp, and C. M. Ramirez. 2012. Trends and causes of severity, size, and number of fires in northwestern California, USA. Ecological applications: a publication of the Ecological Society of America 22:184–203.

North, M. P., R. E. Tompkins, A. A. Bernal, B. M. Collins, S. L. Stephens, and R. A. York. 2022. Operational resilience in western US frequent-fire forests. Forest ecology and management 507:120004.

Sheehan, T., and M. Gough. 2016. A platform-independent fuzzy logic modeling framework for environmental decision support.

Stephenson, N. 1998. Actual evapotranspiration and deficit: biologically meaningful correlates of vegetation distribution across spatial scales. Journal of biogeography 25:855–870.

Stephens, S. L., A. A. Bernal, B. M. Collins, M. A. Finney, C. Lautenberger, and D. Saah. 2022. Mass fire behavior created by extensive tree mortality and high tree density not predicted by operational fire behavior models in the southern Sierra Nevada. Forest ecology and management 518:120258.