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The Costs of Achieving Forest Resilience in California *

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Executive Summary

Wildfires in California have become increasingly severe and costly, prompting a significant policy focus on reducing the risk through forest fuel treatments. We provide a novel spatially explicit analysis of the costs associated with achieving forest resilience in California. Our approach integrates empirical models of treatment choice and treatment costs, generating site-specific estimates of the costs of, and the likelihood that managers would choose, two treatment strategies.

With data from the US Forest Service (USFS) Forest Activity Tracking System and landscape data from the Landscape Fire and Resource Management Planning Tools program, we use hierarchical clustering methods to aggregate USFS activities into two primary treatment types: mechanical thinning and prescribed burns. We then use a choice model to predict which treatment type is selected at each site based on site-specific landscape characteristics. Finally, we estimate per-acre treatment costs for each treatment type by linear regression. To address sample selection bias, we apply a Heckman two-step correction procedure to the cost models.

Our results highlight variability in treatment costs across locations and landscape conditions. On average, mechanical thinning and prescribed burns cost \$577 and \$170 per acre, respectively. We find that mechanical thinning is more commonly applied in areas with higher slopes and elevation; prescribed burns are more likely in flatter areas farther from populated zones. Our cost models indicate that proximity to populated areas, vegetation type, and topography significantly influence treatment costs.

We use our models to project statewide treatment costs for policy scenarios that vary in ambition and identify areas for treatment based on wildfire hazard potential (WHP) and proximity to the wildland–urban interface (WUI). Treating 17 million acres in high-WHP areas is projected to cost \$9.7 billion, and treating only high-WHP areas near the WUI (8.7 million acres) is estimated to cost \$5.0 billion. A hybrid scenario, which includes all moderate-WHP areas near the WUI and high-WHP areas elsewhere, would require treating 30.7 million acres at an estimated cost of \$16.8 billion.

Our analysis is subject to several important limitations. The cost data we use come from

USFS-administered projects, and although they are the most comprehensive available, they may not fully capture costs on private or state lands. Additionally, we do not account for permitting or environmental review costs, which are a major component of overall treatment costs. Moreover, as treatment capacity scales up, increased demand for labor and equipment could raise per-acre treatment costs.

Despite these limitations, our study provides policymakers with critical insights into the spatial heterogeneity and key cost drivers of forest fuel treatments. By offering granular, site-specific cost projections, we aim to support more efficient and cost-effective wildfire mitigation strategies. Our findings suggest that current levels of state and federal funding may be sufficient to achieve the lowest-cost treatment goals, but more ambitious strategies would require substantial increases in funding.

1 Introduction

The frequency and costs of catastrophic wildfires in California and other western states have grown over the past several decades and now constitute a "wildfire crisis" (USDA Forest Service, 2022), resulting from accumulated forest fuels, climate change, and expansion of the wildland–urban interface (WUI). Policy responses emphasize treating forests to reduce their fuel content, modify their structure, and limit the potential for explosive fire behavior. The Inflation Reduction Act alone allocates approximately $4 billion for fuel treatments over a five-year period. Yet fuel treatment needs are vast; the US Forest Service (USFS) Wildfire Crisis Strategy calls for treating 50 million acres of federal, private, and state lands in the west. Funding needs are likely correspondingly immense but not well understood.

Policy and planning efforts toward increasing the pace and scale of fuel treatment require accurate estimates of necessary funding, but policy discourse has generally relied on rough national averages of per-acre treatment costs, which lack much empirical support (Clavet et al., 2021; USDA Forest Service, 2022). Relatively little is known about the overall costs of meeting fuel treatment objectives and maintaining fuel levels over time. A necessary first step in improving the allocation of resources to address the wildfire crisis is a better understanding of these costs and how they vary across forest conditions and location. This study provides such cost estimates for fuel treatment strategies in California. Spatially explicit, empirically based estimates facilitate more accurate estimates of required budgets for accomplishing state-level fuel reduction strategies.

Our estimates of site-specific fuel treatment costs are based on forest management and cost records maintained by the USFS. We use these georeferenced data first to define how combinations of management activities define distinct treatment types—for example, prescribed burning or mechanical treatments—and then to estimate their per-acre costs. The costs for a given site depend on the chosen treatment type; furthermore, the appropriate treatment may change as management alters vegetation. We estimate the costs of treating a given site in California using two sets of models. We first estimate a treatment type choice model in which managers select the best type to use at a given site from a fixed number of options. This choice is assumed to be a function of landscape characteristics that include vegetation type, topographic position, and fuel conditions. Next, we use linear regression to estimate separate cost models for each type. Both the treatment type choice and cost models are estimated using USFS fuel treatment data and a dataset of treatment-specific landscape characteristic variables drawn from the interagency LANDFIRE program and other sources.

We estimate costs of fuel treatments across all forested sites in California using predictions from the type-choice and cost models. This allows us to evaluate costs of a set of scenarios for achieving fuel treatment goals in California that vary in priorities and ambition.

Our study builds on efforts to understand fuel treatment costs. Regression-based cost estimation dates at least to studies of prescribed burning costs in the northern Rockies by Jackson et al. (1982) and González-Cabán & McKetta (1986). Rideout & Omi (1995) examine fuel treatment costs on National Park Service lands using a national database with a focus on the influence of management goals. Berry & Hesseln (2004) apply similar approaches to model costs of prescribed burning and mechanical treatments in the Pacific Northwest and focus on the effects of the WUI. Calkin & Gebert (2006) link biophysical attributes and treatment design characteristics to costs using data from a survey of fire managers in Forest Service Ranger Districts; they emphasize the influence of treatment size on cost estimates. Loomis et al. (2019) use Forest Activity Tracking System (FACTS) data to model the costs of individual treatment activities (rather than full treatments), and their assessment of these data informs our modeling approaches. We incorporate many variables used in the previous studies but with datasets that allow for a more precise definition of treatments, a linkage of treatment attributes to costs, and a more detailed evaluation of costs. Our unique contributions include allowing for endogenous treatment choice and accounting for selection bias in the cost estimates.

This study provides new information on the cost structure of fuel treatments and the resources needed to effectively mitigate wildfire hazards. However, several limitations warrant discussion. First, estimates are based on federal treatment cost data, and these do not include permitting and environmental review costs, a significant component of overall federal treatment costs (Edwards & Sutherland, 2022), and also may not reflect the costs of treating private or state lands. Last, we set out to estimate the total costs of achieving forest resilience for the entire state of California; however, our estimates are based on a partial equilibrium analysis of treatment costs. A comprehensive statewide fuel treatment program would likely involve a large shift in the demand for forest sector labor and specialized capital inputs, which would increase the per-acre costs of treatment, at least in the short to medium term. Still these estimates provide, to our knowledge, the first broad-scale assessment of fuel treatment costs that account for spatially variable landscape features and temporally variable vegetation.

2 Theoretical Framework

The goal of our analysis is to assess the costs and benefits of a fuel treatment regime intended to achieve forest resilience to wildfire in California. Let x_{it} represent the volume of fuels in location i at time t. The objective of fuel treatments is to maintain fuels within an *allowable range*, such that $\underline{x}_i < x_{it} < \bar{x}_i$ may vary across sites, depending on site ecology and fire regimes. Because of this, the allowable range can be changed to be more or less restrictive; it can also be made to be more restrictive nearer to heavily populated areas.

The initial cost of bringing fuels to levels within the allowable range is given by

$$C_t = \sum_{i \ s.t. \ x_{it} > \bar{x}_i} c(x_{it}, \underline{x}_i, m^*(x_{it}, Z_i), Z_i), \tag{1}$$

where $c()$ is a function of current fuel conditions x_{it}, target fuel conditions $\underline{x}_i$, the optimal treatment type m, and site characteristics Z_i. Optimal treatment type is itself a function of current fuel conditions, as, although lower in cost, prescribed fire may not be feasible on sites with high fuel loads. In addition, $c()$ depends on both x_{it} and $\underline{x}_i$—not simply on the difference between x_{it} and $\underline{x}_i$—allowing for the possibility that the costs of fuel treatments are nonlinear in initial fuel volumes. Treatment may not be necessary across the entire state but only on forested sites i where $x_{it} > \bar{x}_i$.

Our procedure for estimating costs of forest maintenance is based on this theoretical framework and proceeds in two steps. First, we estimate the treatment type choice functions $m^*()$ and cost functions $c()$ as a function of site and treatment characteristics. Next, we use this function to calculate predicted treatment costs based on scenarios identifying the area of land identified as in need of fuel treatments.

3 Data

3.1 FACTS Data

Our primary data source for estimating treatment costs is the Hazardous Fuels Treatment polygon data set from the USFS FACTS database. It is a polygon shapefile containing records for treatment activities administered by the agency. As discussed in detail in Knight et al. (2022), treatments often occur as a sequence of activities. For example, a treatment may include distinct activity records for thinning, piling, and burning of piles, where these activities occur over one or multiple years. Following Knight et al. (2022), we consider activities occurring sequentially within the same "footprint"—defined by common polygons and stand unit IDs—to be part of the same treatment. We focus on treatments within California. The FACTS Hazardous Fuels Treatment data set includes some activities that appear to be related to wildfires and postfire management. Because we are more interested in intentional hazard mitigation projects, we remove all treatments that include any activities related to wildfires.[1] We also remove any activities unrelated to fuels management.[2]

FACTS includes no variables to categorize all activities within a treatment into broad treatment types. Because we wish to estimate costs separately within distinct treatment categories, it is necessary to define types based on groups of sequential activities (treatments). We do this using hierarchical cluster analysis, a method for assigning items to groups, where items in each group exhibit greater similarity to each other than to items in other groups (for a related example, see Costanza, Coulston, & Wear, 2017). To improve the performance of the cluster analysis, we drop all activities that appear fewer than 100 times in our California data set (1.1 percent of activities). We then reclassify activity codes for broadcast burning,

[1] Excluded activity codes include those for "Wildfire—-fuels benefit," "Wildland Fire Use," "Wildfire—natural ignition," "Wildfire—human ignition," and "Planned treatment burned in wildfire."

[2] These activities are "Landing treated—Area mitigated," "Stand clearcut (w/ leave trees) (EA/RH/FH)," "Fuel break," "Tree release and weed," "Salvage cut (intermediate treatment, not regeneration)," "Prune," "Sanitation cut," "Improvement cut," "Wildlife habitat precommercial thinning," "Slashing—Pre-site preparation," "Single-tree selection cut (UA/RH/FH)," "Stand clearcut (EA/RH/FH)," "Landing treated—Area mitigated," "Site preparation for planting—manual," and "Site preparation for planting—chemical."

jackpot burning, wildlife habitat prescribed fire as underburning, and thinning for hazardous fuels reduction as precommercial thinning.

We perform the cluster analysis in R using the `hclust` and `vegan` libraries. First, we generate a matrix describing each of the 377 unique combinations of activities that comprise treatments in this modified data set. From this, we calculate a Bray-Curtis dissimilarity matrix using the `vegan` library. Finally, we use the `hclust` library to create treatment clusters based on the dissimilarity matrix and a set of weights indicating the frequency with which each combination of activities appeared within the data set. Several hierarchical clustering agglomeration methods are available. Based on visual inspection of resulting dendrograms, we choose the Ward D2 method, which produces the dendrogram included in Figure 1. In hierarchical cluster analysis, the final number of clusters is determined by the user based on a choice of the "depth" at which to split the resulting dendrogram. We attempt to balance the comprehensibility and parsimony of our classification scheme—which would favor few clusters—against a desire for more uniform treatments within clusters—which would favor more. We find that preliminarily splitting treatments into seven clusters achieves a comprehensible set of treatment types.

The activity types in each cluster are summarized in Panel B of Figure 1. Per-acre treatment costs within each cluster are summarized in Panel C. We calculate treatment costs from activity-level records in the FACTS data set. For some treatments, all activities in the same treatment contain the same cost; we assume this represented the total cost of the treatment. For other treatments, all activities contained unique costs, and we calculate the total cost of the treatment as the sum of all unique costs within the activity. Lacking a clear solution for aggregating cost for the remaining treatments,[3] we dropped them from the data set. These represented about 15 percent of treatments (6,035 of 39,298).

Based on Panel B of Figure 1, a high share of treatments in Clusters 1–3 include burning piled material; however, although Clusters 2 and 3 also include activities to generate piled material, Cluster 1 does not. Correspondingly, Panel C of Figure 1, which illustrates the distribution of per-acre treatment costs within each cluster, indicates relatively low per-acre

[3] The remaining treatments had at least two activities that shared the same cost but at least one other activity with a distinct cost.

costs for Cluster 1. As pile-burning requires that the piles first be created, we view treatment observations in Cluster 1 as likely omitting activities that would have contributed to higher per-acre costs and drop these observations from the remainder of the analysis. Likewise, we drop treatments in Cluster 7; as these most often include commercial thinning activities, it is unclear whether reported costs are net or gross, and average per-acre treatment costs are also relatively low. Treatments in Clusters 4 and 5 are dominated by those including chipping of fuels and precommercial thinning activities, and the large majority of treatments in Cluster 6 include underburning activities. After removing Clusters 1 and 7, we group the remaining clusters into two broad treatment type groups. Treatment costs in Clusters 2–5 are relatively consistent (Panel C), so we group these into a single treatment type that we term "mechanical thinning." We refer to treatments in Cluster 6 as "prescribed burns."

From the activity-level FACTS data, we construct a treatment-level data set, where treatments are categorized based on the two types described. The activity-level data set includes treatment area—measured in acres as the maximum of planned acres among activities in the treatment, the year in which the treatment was begun, and treatment costs (as defined). After the sample exclusions described, our data set includes 7,975 treatment observations.

3.2 Covariates from Landscape Fire and Resource Management Planning Tools (LANDFIRE) and Other Sources

We use LANDFIRE geospatial data products to generate covariates describing fuel, vegetation, fire regime, and topographic characteristics for each FACTS footprint. LANDFIRE is a joint program of the US Department of Agriculture and Department of Interior and provides national 30-m resolution raster layers, which are frequently used to inform and support wildland fire management. LANDFIRE data were initially released in 2001, and since 2008, most layers have been updated approximately once every two years.[4] We calculate treatment covariates based on the most recent release before the first year an activity within a treatment was completed.[5] The topographic rasters are assumed to be time invariant, and

[4]Releases occurred in 2001, 2008, 2010, 2012, 2014, 2016, 2020, 2022, and 2023 (but not 2018).

[5]When the first year of completion aligns with the year of a product release, we use the previous product version (such that an activity completed in 2020 uses product versions from 2016).

therefore the 2020 releases are used to create median elevation, mean aspect, and median slope for all treatment records.

From LANDFIRE data, we calculate statistics describing the existing vegetation type, cover, and condition class, fuel models, aspect, canopy bulk density, elevation, and slope within each treatment area. We calculate the latter three based on the mean values among 30-m raster cells within the treatment area. For aspect, we calculate the circular mean. We calculate measures of existing vegetation type and condition class, fuel models, and fire regime group using the mode for each variable.[6] For each variable, we group values that occurred as the mode infrequently with similar values.[7] We calculate percent existing vegetation cover as the percentage of each treated area with tree, shrub, or herb cover, sparse vegetation cover (indicating density of less than 10 percent), and no vegetation. For tree, shrub, and herb cover, we also calculate the average density (greater than 10 percent) of each category's pixels. Mean canopy bulk density is calculated after removing nonforest value pixels.

Three additional covariates are generated for the FACTS data set based on proximity to other spatial features. Distance to nearest road is calculated using TIGER/Line road shapefiles. Using data and shapefiles from the 2010 decennial census, we calculate distance to the nearest populated census block, where census blocks were categorized as populated if they had a density of greater than 28 people per square mile, the minimum population density to be categorized as WUI according to the definition in the Federal Register.[8] Finally, we generate a variable indicating whether a treatment area intersected threatened or endangered species habitat using habitat areas from the US Fish and Wildlife's Environmental Conservation Online System.

[6]We base fuel models on the 13 Anderson Fire Behavior Fuel Models. For existing vegetation type, we calculate modal types based on type "groups," a coarser categorization than Ecological Systems code, the finest categorization available in the LANDFIRE data.

[7]For existing vegetation type, we assign any classification that occurred as the mode fewer than 100 times to an "Other" category. We also combine into single categories the eight "Developed" categories (developed areas), three "Transitional" categories (transition vegetation), and two "Grassland" categories (grassland and steppe areas). Aggregating these four types resulted in 15 categories, simplified from an initial 45. For vegetation condition class, we combine "High" (198 observations) and "Very High" (seven observations) departure areas with "Low" departure areas. Additionally, where vegetation condition class had generated a missing value, we replaced it with a new "No Vegetation Departure" value.

[8]Both distance to nearest road and distance to nearest populated census block are binned into categories (less than 0.1 km, 0.1–0.5 km, and 0.5–1.25 km and 1 km, 1–5 km, and greater than 5 km, respectively).

In addition to covariate measurements within treated areas, accounting for sample selection in our models of treatment costs and projecting treatment costs across yet untreated areas each requires covariate measurements for areas not yet selected for treatment. Those for treated areas are based on averages within FACTS footprints, which reduces noise in the FACTS-level covariate measurements. To be consistent with these measurements, we measure characteristics of untreated cells using local averages of 30-m LANDFIRE variables and other covariate variables. For each variable, we use the `focal` function from R's `terra` package to calculate circular moving window averages corresponding to the averages calculated within each FACTS treatment. For example, we measure slope for each treatment area based on median slope value within the treatment footprint; correspondingly, we calculate median slope within a moving window around each 30-m LANDFIRE raster cell. We set the size of the moving window equal to 381,957 square meters (approximately 94 acres), the mean area of a treatment within our FACTS data set.

For the sample of untreated cells used in the sample selection models of treatment costs, we draw a stratified random sample of pixels from the "smoothed" rasters described earlier. First, we divide California into a hexagonal grid of 8,830 50-km^2 cells. From each cell, we randomly sample a single pixel from the set that could reasonably have been a candidate to receive a fuel treatment but did not. Therefore, we identify within each cell the pixels that (1) have not received fuel treatment, (2) are on USFS lands, (3) are not within designated wilderness areas, and (4) do not have slope, elevation, or distance from roads greater than the maximum values observed for treatments within our FACTS data set. Some hexagonal cells have no pixels meeting these criteria; in the end, our sample includes 2,526 untreated pixels. Because pixel characteristics are drawn from rasters describing characteristics of the landscape within a 381,957-sq. m buffer around each pixel, the characteristics summarize average landscape characteristics within a hypothetical treatment centered on the pixel.

Table 1 reports summary statistics for untreated pixels and treatments in Groups 1 and 2. Treated areas tend to be somewhat flatter, higher in elevation, and nearer to roads and populated areas. They are also more likely to intersect endangered species habitat and have higher canopy bulk density. On average, treated areas have far higher percent tree cover (75 and 81 percent in Types 1 and 2, respectively) than untreated areas (24 percent). A significantly higher share of untreated areas have high to very high vegetation departure relative to treated areas. Treatments in Type 2 were more likely to be further from populated areas. Douglas Fir-Grand Fir-White Fir was the most common vegetation type in both treatment types; however, 41 percent of Type 2 treatments occurred in it, compared to 26 percent for Type 1. The most common type for untreated areas was Chaparral.

4 Methods

4.1 Treatment Choice and Cost Models

We estimate the costs of fuel removal on a given pixel in two stages. First, using estimates from a discrete choice model of fuel treatment type choice, we predict which variety of fuel treatment will be used on a given pixel. Then, we predict treatment costs for the pixel based on estimates of treatment type-specific cost functions.

4.1.1 Treatment Type Choice

We assume that, conditional on the decision to treat pixel i, managers will choose treatment type $m \in \{1, 2\}$ if the per-acre costs C_{im} of using treatment type m on pixel i are lower than the costs of any alternative treatment type C_{il} :

$$C_{im} < C_{il} \quad \forall m \neq l \in \{1, 2\}, \tag{2}$$

where $C_{im} = X_i \beta^m + \varepsilon_{im}$, X_i' is a vector of observable characteristics of pixel i, and ε_{im} is a vector of unobserved characteristics. Under the assumption that ε_{im} is distributed Type 1 extreme value, the probability that treatment type m is chosen on pixel i can be written

$$\Pr(\varepsilon_{il} - \varepsilon_{im} > X_{im}'\beta - X_{il}'\beta \quad \forall m \neq l \in \{1, 2\}) = \frac{\exp(X_{im}'\beta^m)}{\sum_{l=1}^{2} \exp(X_{il}'\beta^l)} \tag{3}$$

We use (3) to estimate β^m by maximum likelihood, including in the vector X_{im} topographic variables, variables describing vegetation and fuel conditions, distances to roads and developed or WUI areas, and an indicator variable for whether the treatment intersects threatened or endangered species habitat.

4.1.2 Cost Functions

For each treatment type, we estimate type-specific cost functions based on the same set of attributes used to determine type choice. The sample of sites at which we observe costs is selected, because managers only choose to treat sites with high values of treatment relative to costs. If this choice is driven partly by unobserved factors that also affect costs—for example, if managers selectively choose sites where unobserved factors result in lower costs—failing to account for selection in the sample could result in biased cost function estimates.

We denote the choice to treat ($m \in \{1, 2\}$) with the binary variable T, where $T = 0$ if a site is not treated ($m = 0$) and $T = 1$ otherwise. Managers choose to treat a site if

$$X_i'\delta + \nu_i > 0. \tag{4}$$

For treated sites, we observe per-acre treatment costs, which we assume are determined according to the per-acre cost function:

$$\ln(C_{im}) = X_i\gamma^m + u_{im}. \tag{5}$$

Selection bias occurs because

$$\mathrm{E}\big(\ln(C_{im})|\nu_i > -X_i'\delta, X_i\big) = X_i\gamma^m + \mathrm{E}\big(u_{im}|\nu_i > -X_i'\delta, X_i\big), \tag{6}$$

and $\mathrm{E}\big(u_{im}|\nu_i > -X_i'\delta, X_i\big)$ is not equal to zero if u_{im} and ν_i are correlated.

To account for selection in our estimates of costs, we use the Heckman two-step correction procedure. We begin by assuming that u_{im} and ν_i are independent of X_i, ν_i is distributed standard normal, and u_{im} is distributed normally with variance σ_u. Under these assumptions,

$$\mathrm{E}\big(u_i|\nu_i > -X_i'\delta, X_i\big) = \rho\sigma_u \frac{\phi(X_i\delta)}{\Phi(X_i\delta)}, \tag{7}$$

where ρ is the correlation between u_{im} and ν_i. The first step of the Heckman correction is to estimate the parameters of Equation 4 based on characteristics of sites chosen and not chosen for treatment. We include sites chosen through either type in the first-stage equation. We then use estimates from the first stage to calculate the inverse Mills ratio ($\frac{\phi(X_i\delta)}{\Phi(X_i\delta)}$), which we use in the second stage to account for selection. The second-stage equation is written as

$$ln(C_{im}) = X_i\gamma^m + \gamma_\lambda \frac{\phi(X_i\delta)}{\Phi(X_i\delta)} + e_{im}, \tag{8}$$

where $\gamma_\lambda = \rho\sigma_u$. A difference between our case and standard applications of the Heckman two-step procedure is that we estimate second-stage cost functions for both treatment types. Our implicit assumption is that selection bias operates through the choice to treat or not rather than through choices of specific treatment types.

4.2 Treatment Choice and Cost Projections

With our functions for treatment type choice and cost (in Table 2 and Table 3), we project which fuel treatment will be used for each pixel and the cost of each for that pixel. We use the most recent version LANDFIRE raster for each of the covariates in our functions. We use the 2023 rasters for fuel models, existing vegetation cover, existing vegetation type, and canopy bulk density. Raster data from 2023 were not available for fire regime group and vegetation condition class, so we use the most recent available data (2020 and 2022, respectively). As with the covariates in Section 4.2, we use the 2020 releases for the time-invariant slope and elevation topographical rasters. We also create rasters for our three additional covariates—distance to nearest road, distance to nearest populated block, and intersection with threatened or endangered species habitats. Using the same method as described in Section 4.2, we calculate average (mean, median, or mode) covariate values within a circular moving window around each pixel. Windows are 381,957 sq. m in area, the average size of treatments in our FACTS data set.

Finally, we apply each of the coefficients in our treatment type choice and cost functions to the smoothed rasters, which produces rasters indicating the percent chance of choosing prescribed burns, cost per acre of mechanical thinning, and cost per acre of prescribed burns.[9]

[9]As an interim step in calculating our per-acre cost rasters, we calculate rasters for the unadjusted per-acre

5 Results

5.1 Strategy Choice and Treatment Cost Model Estimates

5.1.1 Strategy Choice

The estimates from the treatment type choice models are reported in Table 2. Coefficients can be interpreted as the change in the log odds of choosing Type 2 (prescribed burn) relative to Type 1 (thinning) given a one-unit change in a given variable. For example, Table 2 indicates that if slope increases by 1 degree, the log odds of a prescribed burning being chosen over thinning increase by 0.04: prescribed fire is preferred on steeper slopes. Likewise, the odds of prescribed fire increases for lower elevation areas, places further from populated areas, and areas with lower canopy bulk density. The relative odds of burning over thinning treatments are highest in juniper woodlands and sagebrush shrubland and steppe.

5.1.2 Cost Functions

Estimates of cost functions for each of the three treatment types are reported in Table 3. The first two columns report estimates from OLS regressions of log per-acre costs on site characteristics. Per-acre treatment costs vary substantially, even within treatment types, so the cost models have only moderate predictive power: R-squared values for the two models are 0.13 and 0.20. For thinning treatments, sites that are flatter, farther from populated areas, and less highly departed (low versus moderate VCC) have lower costs. For example, a one degree increase in a site's average slope increases cost by about 1 percent. Prescribed burn treatments decline in cost with increases in slope and are higher cost at higher elevations and areas nearer to populated census blocks.

The third column reports results from the Heckman first-stage regression, a probit regression of the probability of choosing to treat a site. As might be expected, the likelihood of treating a site declines with distance from roads and distance to the nearest populated area. The regression reported in the third column is used to calculate an inverse Mills ratio. This is included in the fourth and fifth column regressions, which are modified versions of the

treatment costs and a raster for the first stage of the Heckman procedure. With these rasters, we are able to adjust the costs with our corrections to derive our final per-acre cost with the second-stage equation.

first and second column regressions that account for selection bias. Although explanatory power does not change substantially from Columns (1) and (2) to (3) and (4), many of the coefficients change in magnitude. For example, accounting for selection bias increases the effect of proximity to roads and populated areas on costs, for both Types 1 and 2.

5.2 Treatment Choice and Cost Projections

Figure 2 shows projected treatment type choices, per-acre costs of treating for each type, and expected costs given estimated probabilities of choosing each type. The map, coupled with examination of variation in the distributions of explanatory variables across areas with very high and very low probabilities of choosing prescribed fire (Figure A.1), suggests that prescribed burns are more likely to be chosen in lower elevation and flatter areas. They are also somewhat more likely to be chosen in areas farther from a populated census block, and their likelihood of being chosen varies substantially across vegetation types.

Thinning treatments cost more on average, with mean projected per-acre costs of approximately $577; they are highest near the Pacific coast in northern California and parts of the Sierra Nevada and San Bernardino ranges and lowest in northeastern California and the southern desert. Based on variation in explanatory variables across areas with high and low thinning costs (Figure A.2), differences in cost appear to be driven mainly by differences in slope, distance to populated census blocks and roads, and canopy bulk density. Prescribed burn costs are generally significantly lower, with a mean of approximately $170 per acre; however, they appear to be higher near more heavily populated areas in southern California and the Bay Area. This is confirmed by Figure A.3, which shows that areas with relatively high costs of prescribed burning tend to be closer to roads and populated areas.

Projected per-acre costs for both treatment types are somewhat lower than standard engineering-based cost estimates and mean per-acre treatment costs within the FACTS data. This discrepancy could be partly explained by composition effects due to differences between places where treatments have been implemented and the broader set of cells in California over which we are projecting costs. However, it is also likely at least partly due to the cost models' difficulty in predicting very high treatment costs. The distributions of cost per acre and log cost per acre are skewed; although the models perform well for treatments with low or moderate costs, they systematically underpredict for high-cost treatments. Future work could seek to improve the model fit for treatments with very high costs or use random draws from the distributions of cost residuals to improve the match between the projected and observed cost distributions.

5.3 Evaluation of Statewide Treatment Strategies

To demonstrate application of the treatment choice and cost functions to program planning for California, we evaluate a set of rule-based treatment scenarios using WHP and/or proximity to developed areas (the WUI, defined based on wildland–urban intermix and interface areas within the most recent SILVIS data product). The highest WHP (defined as the top quartile of WHP scores) accounts for 17 million acres that would cost $9.7 billion (Figure 3). Treating only high-WHP areas within 1.5 miles of the WUI (8.7 million acres) would cost $5.0 billion. Moderate-WHP areas (top three quartiles of WHP scores) amount to 45.4 million acres and would cost $24.0 billion; 21.5 million acres of moderate-WHP forests are found near WUI and would cost $12.1 billion. A hybrid scenario that treats all moderate-WHP areas near WUI and high-WHP areas elsewhere includes 30.7 million acres and would cost $16.8 billion. Average costs range from $530/acre for the "moderate-WHP" scenario to $580/acre for the "high-WHP near WUI" scenario.

6 Discussion

California appropriated an annual average of $275 million for hazardous fuel treatments and $192 for fuel breaks between 2021 and 2024 (Petek, 2024). In 2020, the USFS and California entered into a shared stewardship agreement to expand fuel treatments to 1 million acres per year by 2025, with both committing to treat 500,000 acres annually.[10] Assuming that, consistent with this agreement, the USFS matches California's current annual spending on hazardous fuel treatments,[11] our estimates suggest that present levels of spending are

[10] Agreement for Shared Stewardship of California's Forest and Rangelands between the State of California and the USDA, Forest Service Pacific Southwest Region, `https://www.gov.ca.gov/wp-content/uploads/2020/08/8.12.20-CA-Shared-Stewardship-MOU.pdf`

[11] Federal appropriations for all US hazardous fuels management totaled $649 million in 2024 (including $166.8 million supplemental appropriations from the Infrastructure Investment and Jobs Act; Riddle 2024).

commensurate with achieving treatment goals laid out under our lowest-cost scenario over a 10-year period. If California and the USFS were to each spend at California's current rate of $275 million per year, it would be sufficient to cover the $5 billion to treat all high-WHP areas within 1.5 miles of the WUI over 10 years.

However, our cost estimates should be understood in light of several limitations. First, our data on costs are administrative data from the USFS and reflect treatments administered on its lands. Although these data are the best and most comprehensive available on fuel treatment costs, they may not reflect those of other federal agencies or private or state lands. Furthermore, the FACTS data set does not report the full costs of fuel treatments on USFS lands; in particular, it is missing indirect costs of planning (including environmental reviews) and overseeing treatment activities. Arguably, the omission of federal planning and monitoring costs should cause our per-acre planning costs to better reflect fuel treatment costs on nonfederal lands; nevertheless, their omission biases downward estimates of federal treatment costs.[12] Our estimates also do not account for the potential for commercial thinning treatments, as appropriate cost measurements would be net of revenues generated. Although we expect that such treatments are not economically feasible throughout much of California (Wear, Wibbenmeyer, & Joiner, 2024), they should lower overall program costs to the degree they are practicable. Last, it is possible that effectively reducing fire hazard does not require treating all the lands identified under each scenario; interrupting and reducing fire spread may require treating only a subset of lands.

A hypothetical, but not unrealistic, overhead rate of 50 percent for planning and oversight implies a total budget burden (across federal, state, and private lands) of approximately $750 million per year to achieve the lowest-cost scenario in Figure 3 in ten years—treating about 870,000 acres per year—and approximately $3.6 billion for the highest-cost scenario. The portion of the landscape it is necessary to treat to effectively reduce wildfire hazard is unknown, but may be as low as 20–30 percent (Oliveira et al., 2016).

Assuming the share of acres it is necessary to treat is 30–50 percent, and inflating cost es-

Based on accomplished treatment acres in 2023, approximately 20–45 percent of recent federal fuel treatment appropriations have been directed to California, suggesting that recent federal spending there has been similar in magnitude but somewhat lower than the state's own spending.

[12] However, the costs of monitoring treatments, such as patrolling prescribed burns, would likely be higher near WUI areas and potentially higher for the state.

timates from Figure 3 to account for overhead, we estimate that implementing the treatment scenarios described in Section 5.3 would cost \$225–\$375 million per year for the least-costly and \$1.1–\$1.8 billion per year for the most-costly scenario. Combined current spending by the state and federal governments may be sufficient to achieve the least-cost option considered here, but implementing fuel treatments throughout all moderate-WHP areas within the state would require a 100–200 percent increase in annual spending on fuel treatments.[13]

However, costs may increase further were fuel treatment programs to sharply increase in scope. In the 10 years leading up to the 2020 shared stewardship agreement, 175,000–300,000 acres had been treated each year (Knight et al., 2022). The recent shared stewardship's target of 1 million acres per year exceeds the number of required acres under the "High-WHP near WUI" scenario, but achieving treatment goals of other scenarios would require further expanding the scale of operations. Our model assumes that per-acre costs are constant in the overall scale of treatment operations; however, it is possible that an outward shift in demand for forest management will result in higher per-acre costs. The general equilibrium cost consequences of large-scale increases in the pace and scale of fuel treatment are therefore an important topic for future research.

Although additional research is needed to further support the economic analysis of fuel treatment options, our empirical treatment choice and cost models provide practical tools for estimating costs at management and policy levels. They offer fine-grained estimates of costs for planners and can be scaled up to estimate implications for federal and state appropriations. We find generally that, although costly, ambitious fuel treatment strategies would not require orders of magnitude increases in state and federal appropriations. These cost models could be paired with empirical estimates of treatment outcomes to support comprehensive cost–benefit analysis of strategies to help guide program design in California.

[13]This is based on assumed status quo spending of \$275 per year by both the state and federal governments.

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Table 1: Fuel treatment summary statistics, by group

	Untreated		Cluster 1		Cluster 2	
	Mean	Std. Err.	Mean	Std. Err.	Mean	Std. Err.
Slope (degrees)	15	(0.17)	11	(0.09)	12	(0.14)
Median Elevation (km)	1.4	(0.01)	1.5	(0.01)	1.5	(0.01)
Distance to Roads (km)	.62	(0.01)	.073	(0.00)	.1	(0.01)
Distance to Populated Census Block (km)	6.8	(0.12)	4.9	(0.08)	5.7	(0.13)
ES Habitat Intersection	.19	(0.01)	.22	(0.01)	.32	(0.01)
Percent Herb Cover	2.3	(0.12)	7.3	(0.24)	6.5	(0.33)
Percent Nonvegetation	.044	(0.00)	8.1	(0.26)	5	(0.28)
Percent Shrub Cover	12	(0.24)	9	(0.27)	6.8	(0.33)
Percent Sparse Vegetation Canopy (< 10%)	.021	(0.00)	.58	(0.04)	.49	(0.04)
Percent Tree Cover	24	(0.41)	75	(0.43)	81	(0.55)
Canopy Bulk Density	5.3	(0.09)	5.8	(0.05)	5.9	(0.08)
Existing Vegetation Type						
Alpine Dwarf-Shrubland, Fell-field and Meadow	.025	(0.00)	.0095	(0.00)	.0048	(0.00)
California Mixed Evergreen Forest and Woodland	.067	(0.00)	.047	(0.00)	.047	(0.00)
Chaparral	.31	(0.01)	.11	(0.00)	.087	(0.01)
Conifer-Oak Forest and Woodland	.045	(0.00)	.044	(0.00)	.031	(0.00)
Developed Low-Med-High Intensity	.0083	(0.00)	.11	(0.00)	.061	(0.00)
Douglas-fir-Grand Fir-White Fir Forest and Woodland	.16	(0.01)	.26	(0.01)	.41	(0.01)
Douglas-fir-Ponderosa Pine-Lodgepole Pine Forest and Woodland	.072	(0.01)	.16	(0.00)	.16	(0.01)
Grassland and Steppe	.0004	(0.00)	.0055	(0.00)	.01	(0.00)
Juniper Woodland and Savanna	.02	(0.00)	.016	(0.00)	.0044	(0.00)
Other	.1	(0.01)	.07	(0.00)	.034	(0.00)
Ponderosa Pine Forest, Woodland and Savanna	.024	(0.00)	.072	(0.00)	.055	(0.00)
Red Fir Forest and Woodland	.053	(0.00)	.056	(0.00)	.057	(0.00)
Sagebrush Shrubland and Steppe	.083	(0.01)	.0099	(0.00)	.0052	(0.00)
Transitional Forest-Herb-Shrub	0	(.)	.014	(0.00)	.0072	(0.00)
Western Oak Woodland and Savanna	.032	(0.00)	.022	(0.00)	.022	(0.00)
Vegetation Condition Class						
High to Very High, 67–100	.15	(0.01)	.032	(0.00)	.029	(0.00)
Low to Mod., 17–33	.18	(0.01)	.37	(0.01)	.42	(0.01)
Mod. to High, 51–66	.27	(0.01)	.098	(0.00)	.079	(0.01)
Mod. to Low, 34–50	.4	(0.01)	.46	(0.01)	.46	(0.01)
No Veg. Departure	.0012	(0.00)	.017	(0.00)	.0056	(0.00)
No. of observations	2,526		5,481		2,494	

Table 2: Treatment choice function estimates

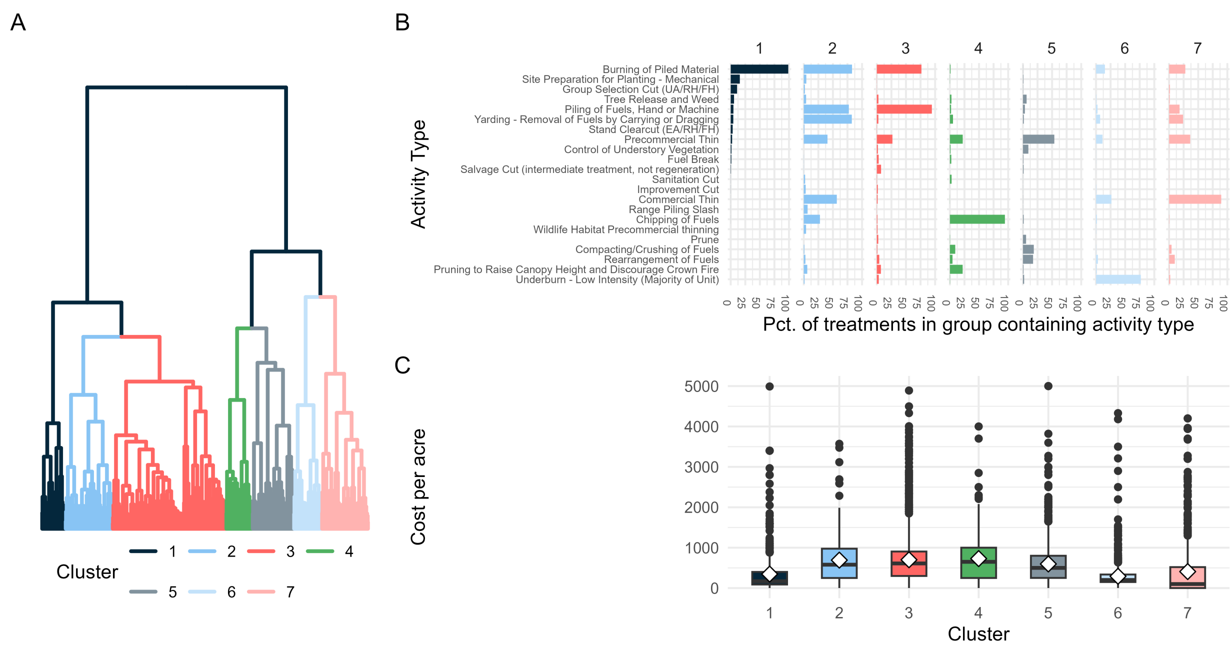
	Coef.	t-stat.
Slope (degrees)	-0.0371**	[-6.42]
Median Elevation (km)	-0.591**	[-5.98]
Distance to Road [Base Case: 0–0.1 km]		
0.1–0.5 km	-0.468**	[-4.30]
> 0.5 km	-0.369*	[-2.27]
Distance to Populated Area [Base Case: 0–1 km]		
1–5 km	0.330**	[3.72]
5–10 km	0.280**	[2.80]
10–40 km	0.477**	[4.30]
ES Habitat Intersection	-0.0684	[-0.83]
Percent Herb Cover	-0.00309	[-1.18]
Percent Nonvegetation	-0.00693+	[-1.83]
Percent Shrub Cover	-0.000930	[-0.41]
Percent Sparse Vegetation Canopy (< 10%)	0.0184+	[1.67]
Canopy Bulk Density	0.0292*	[2.43]
Existing Vegetation Type [Base Case: Douglas Fir-Grand Fir]		
Alpine Dwarf-Shrubland, Fell-field and Meadow	-0.766	[-1.26]
California Mixed Evergreen Forest and Woodland	0.293	[1.52]
Chaparral	0.0857	[0.57]
Conifer-Oak Forest and Woodland	0.350*	[2.13]
Developed Low-Med-High Intensity	-1.035**	[-4.52]
Douglas-fir-Ponderosa Pine-Lodgepole Pine Forest and Woodland	0.417**	[4.44]
Grassland and Steppe	-0.309	[-0.62]
Juniper Woodland and Savanna	1.057**	[4.54]
Other	-0.196	[-1.23]
Ponderosa Pine Forest, Woodland and Savanna	0.891**	[6.99]
Red Fir Forest and Woodland	-0.569**	[-2.94]
Sagebrush Shrubland and Steppe	1.819**	[6.35]
Western Oak Woodland and Savanna	-0.282	[-1.13]
Vegetation Condition Class [Base Case: None to Moderate Departure, 0–33%]		
High to Very High, 67–100	0.602**	[3.53]
Mod. to High, 51–66	-0.320*	[-2.39]
Mod. to Low, 34–50	0.0797	[1.06]
Constant	-0.828**	[-3.76]
No. of observations	7,739	
Pseudo R-squared	0.0757	

Notes: Estimates are from a logit model of treatment strategy choice, where the outcome is a binary variable indicating selection of treatment in Strategy 2 (prescribed fire) over a treatment in Strategy 1 (thinning). Coefficients can be interpreted as marginal effect of an increase in a given variable on the log odds that Strategy 2 will be chosen over Strategy 1.

Table 3: Treatment cost functions

	OLS Treatment Type 1	OLS Treatment Type 2	Heckman First-Stage	Heckman Treatment Type 1	Heckman Treatment Type 2
Slope (degrees)	0.0103**	-0.00851*	-0.00437	0.00963**	-0.0123**
	[6.00]	[-2.14]	[-0.95]	[5.43]	[-2.81]
Median Elevation (km)	0.0868**	0.182*	-0.112	0.0631+	0.0851
	[2.76]	[2.57]	[-1.45]	[1.80]	[1.00]
Distance to Road [Base Case: 0–0.1 km]					
0.1–0.5 km	0.0230	0.0231	-1.190**	-0.199	-0.947*
	[0.75]	[0.32]	[-20.46]	[-1.34]	[-1.99]
> 0.5 km	-0.0788+	-0.133	-1.219**	-0.307*	-1.138*
	[-1.68]	[-1.17]	[-18.37]	[-1.97]	[-2.27]
Distance to Block [Base Case: 0–1 km]					
1–5 km	-0.0720*	-0.131*	-0.324**	-0.131**	-0.389**
	[-2.50]	[-2.18]	[-4.16]	[-2.73]	[-2.80]
5–10 km	-0.157**	-0.235**	-0.683**	-0.282**	-0.783**
	[-4.78]	[-3.45]	[-7.20]	[-3.20]	[-2.85]
10–40 km	-0.319**	-0.162*	-0.497**	-0.410**	-0.561**
	[-8.41]	[-2.12]	[-5.51]	[-5.80]	[-2.70]
ES Habitat Intersection	0.0364	0.0249	0.163+	0.0655*	0.160+
	[1.43]	[0.44]	[1.88]	[2.07]	[1.85]
Percent Herb Cover	0.000781	0.000183	0.0333**	0.00657+	0.0258*
	[1.05]	[0.10]	[6.61]	[1.71]	[2.05]
Percent Nonvegetation	0.000473	0.0103**	-0.0312**	-0.00491	-0.0139
	[0.49]	[3.51]	[-8.88]	[-1.35]	[-1.15]
Percent Shrub Cover	-0.00137+	-0.00225	0.0327**	0.00437	0.0236+
	[-1.88]	[-1.29]	[11.39]	[1.15]	[1.86]
Percent Sparse Vegetation Canopy (< 10%)	-0.00416	0.00160	-0.0683**	-0.0171+	-0.0528+
	[-1.07]	[0.20]	[-3.69]	[-1.84]	[-1.91]
Canopy Bulk Density	0.00355	0.00476	-0.00916	0.00146	-0.00301
	[0.88]	[0.51]	[-0.90]	[0.34]	[-0.30]
Existing Vegetation Type [Base Case: Douglas Fir-Grand Fir]					
Alpine Dwarf-Shrubland, Fell-field and Meadow	-0.0951	-1.146**	-1.153**	-0.297+	-2.056**
	[-0.83]	[-3.04]	[-4.57]	[-1.70]	[-3.54]
California Mixed Evergreen Forest and Woodland	0.0767	-0.215	-0.428**	-0.00867	-0.568**
	[1.21]	[-1.58]	[-3.37]	[-0.10]	[-2.60]
Chaparral	-0.185**	0.125	-1.046**	-0.369**	-0.702+
	[-4.05]	[1.20]	[-7.68]	[-2.87]	[-1.70]
Conifer-Oak Forest and Woodland	-0.159**	0.0180	0.0884	-0.144*	0.0871
	[-2.69]	[0.16]	[0.68]	[-2.41]	[0.73]
Developed Low-Med-High Intensity	-0.264**	-0.0953	2.020**	0.0715	1.392+
	[-4.92]	[-0.57]	[7.12]	[0.32]	[1.88]
Douglas-fir-Ponderosa Pine-Lodgepole Pine Forest and Woodland	-0.0778*	-0.111+	0.140	-0.0514	0.000138
	[-2.34]	[-1.81]	[1.60]	[-1.37]	[0.00]
Grassland and Steppe	-0.0151	0.562	-0.926**	-0.174	-0.149
	[-0.12]	[1.45]	[-2.73]	[-1.08]	[-0.29]
Juniper Woodland and Savanna	-1.089**	-0.296*	-0.00223	-1.084**	-0.288*
	[-9.69]	[-2.21]	[-0.02]	[-9.64]	[-2.15]
Other	-0.102*	-0.166	-0.529**	-0.196*	-0.591*
	[-2.05]	[-1.55]	[-3.09]	[-2.48]	[-2.54]
Ponderosa Pine Forest, Woodland and Savanna	-0.288**	-0.388**	-0.0222	-0.290**	-0.400**
	[-5.54]	[-4.94]	[-0.14]	[-5.57]	[-5.10]
Red Fir Forest and Woodland	-0.0563	0.143	-0.122	-0.0775+	0.0393
	[-1.25]	[1.10]	[-1.07]	[-1.65]	[0.28]
Sagebrush Shrubland and Steppe	-0.693**	-1.066**	-1.258**	-0.913**	-2.063**
	[-4.57]	[-6.08]	[-7.40]	[-4.37]	[-4.01]
Western Oak Woodland and Savanna	-0.173*	0.331+	-0.487**	-0.264**	-0.0514
	[-2.35]	[1.82]	[-2.61]	[-2.79]	[-0.20]
Vegetation Condition Class [Base Case: None to Moderate Departure, 0–33%]					
High to Very High, 67-100	0.0162	-0.0984	-0.261**	-0.0315	-0.324*
	[0.24]	[-0.91]	[-2.67]	[-0.43]	[-2.10]
Mod. to High, 51–66	-0.0761+	0.131	-0.246**	-0.119*	-0.0703
	[-1.77]	[1.41]	[-3.20]	[-2.32]	[-0.52]
Mod. to Low, 34–50	0.0171	0.120*	0.126+	0.0409	0.226**
	[0.71]	[2.30]	[1.87]	[1.43]	[3.09]
Inverse Mills Ratio				0.203	0.880*
				[1.53]	[2.06]
Constant	6.740**	6.844**	-2.342**	6.198**	4.486**
	[9.31]	[10.41]	[-12.03]	[7.69]	[3.40]
No. of observations	4,877	1,035	8,382	4,877	1,035
R-squared	0.126	0.201		0.126	0.205
Pseudo R-squared			0.273		

Figure 1: Results of hierarchical cluster analysis of fuel treatment activities



Note: Panel A shows a dendrogram of the cluster analysis, produced based on the Ward D2 method. The dendrogram is split at a depth chosen to produce seven clusters. Panel B displays the percentage of treatments in group cluster containing each in a series of activity types; activity types that were present in no more than 2.5 percent of treatments in any cluster are not shown. Panel C is a box plot of total treatment costs per acre within each cluster. The box contains the central 50 percent of observations with respect to treatment cost; outliers are observations more than 1.5 IQR above the 75th percentile of cost. Treatments with reported per-acre costs greater than $5,000 are dropped.

Figure 2: Projections of strategy choice and per-acre treatment cost within California

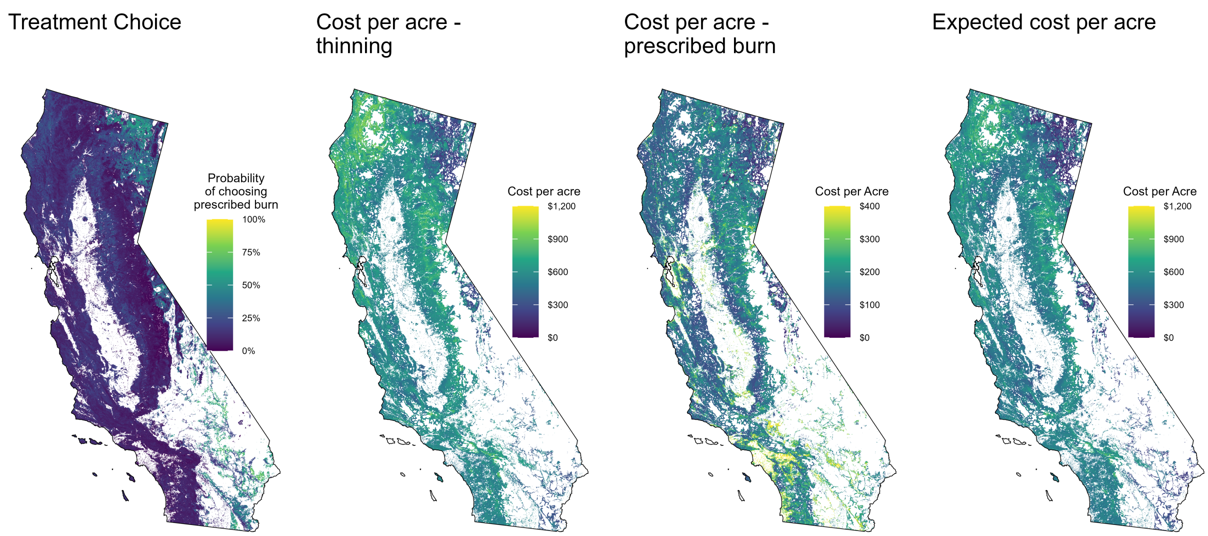
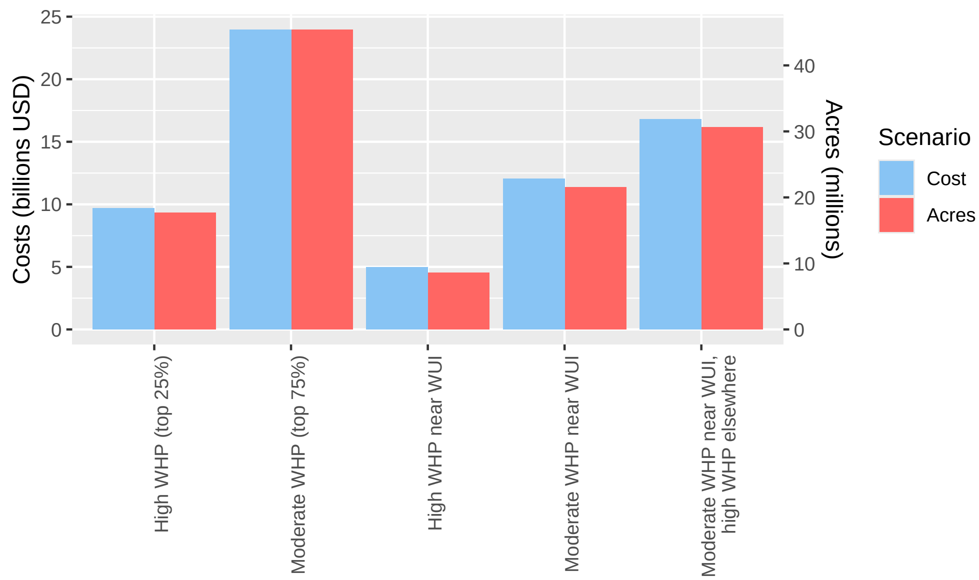
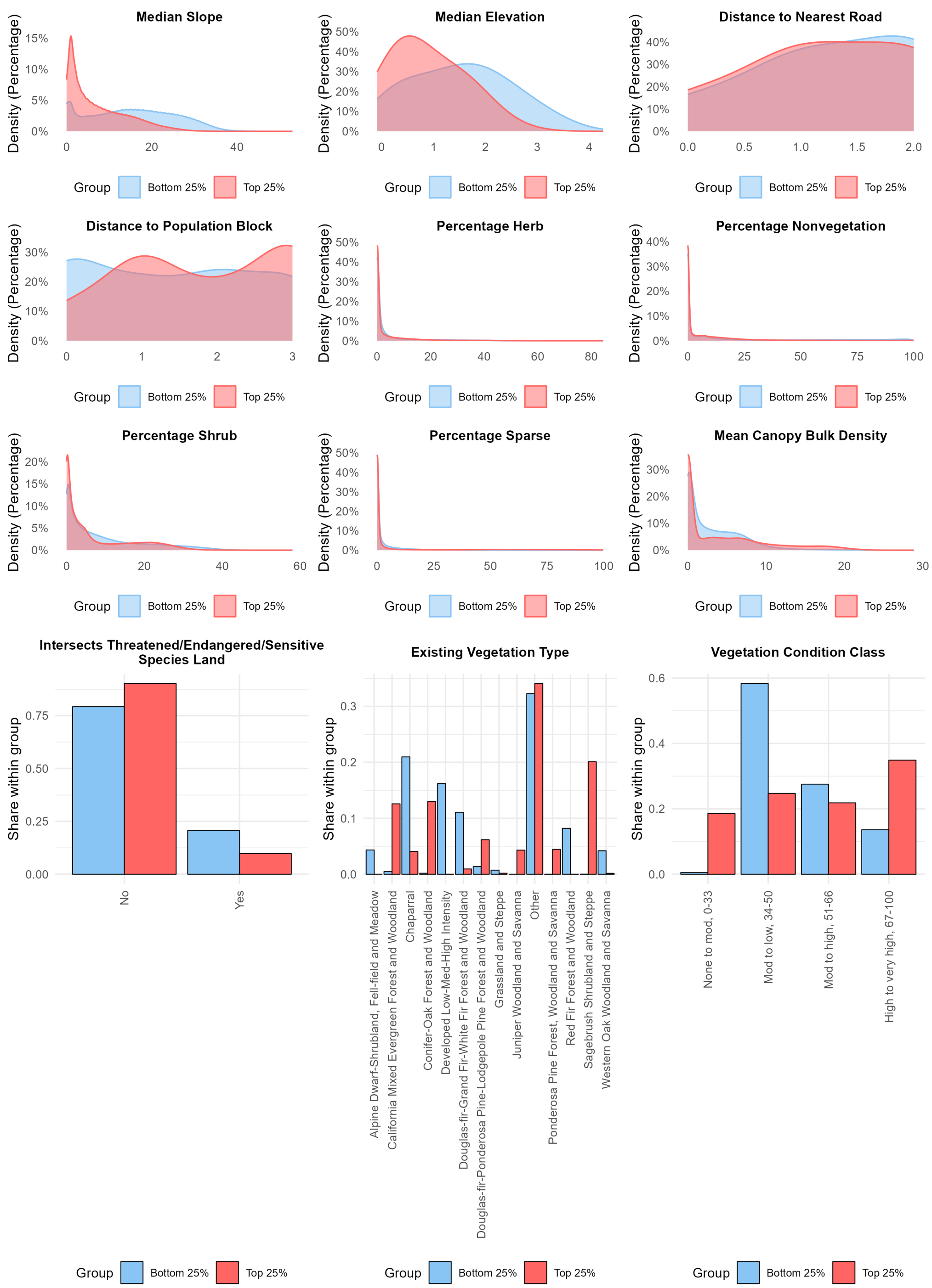


Figure 3: Projected costs and acres treated for five California treatment scenarios



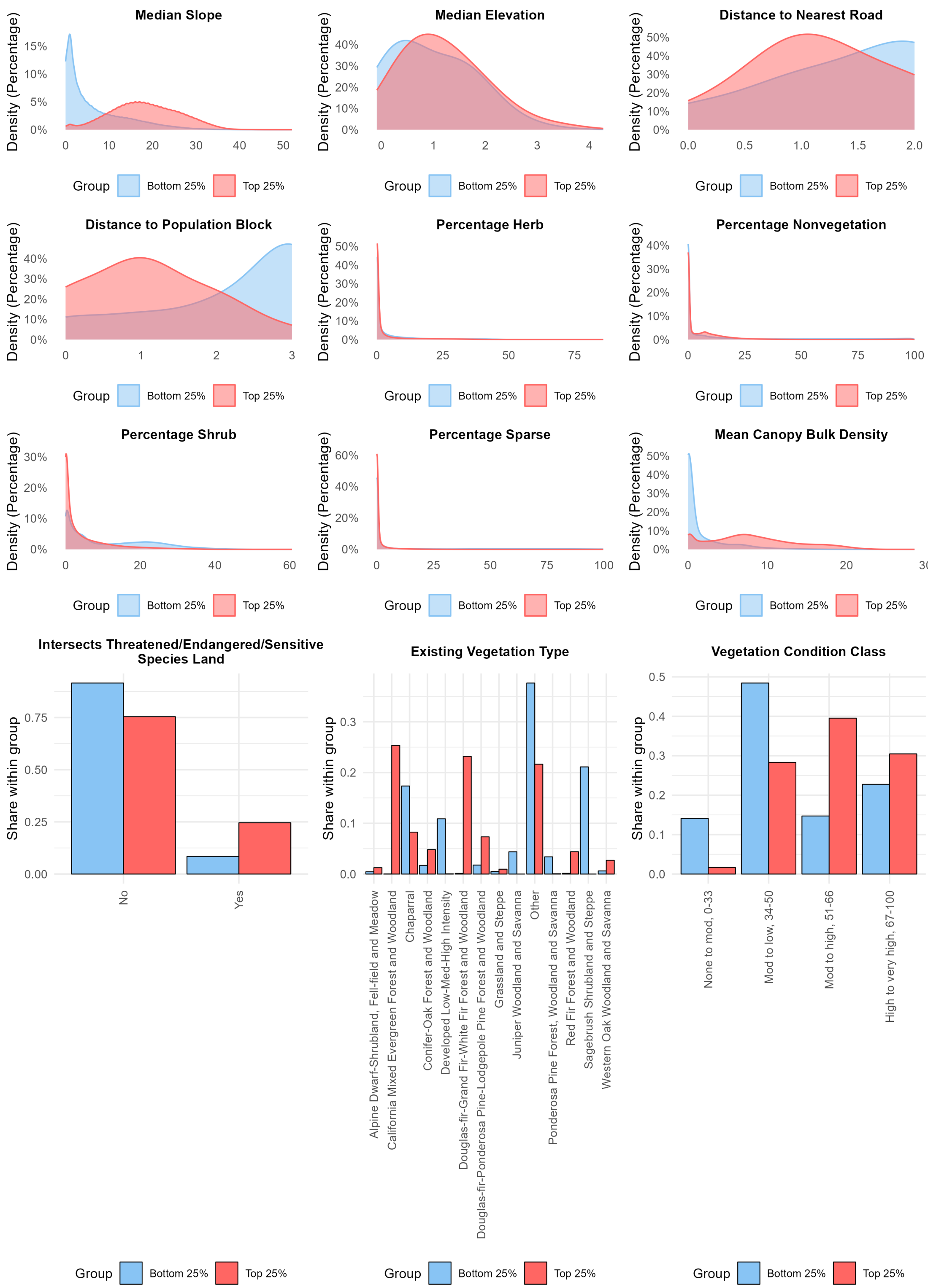
A Additional Tables & Figures

Figure A.1: Distributions of explanatory variables for pixels within the top and bottom quartiles of predicted probability of choosing prescribed burn



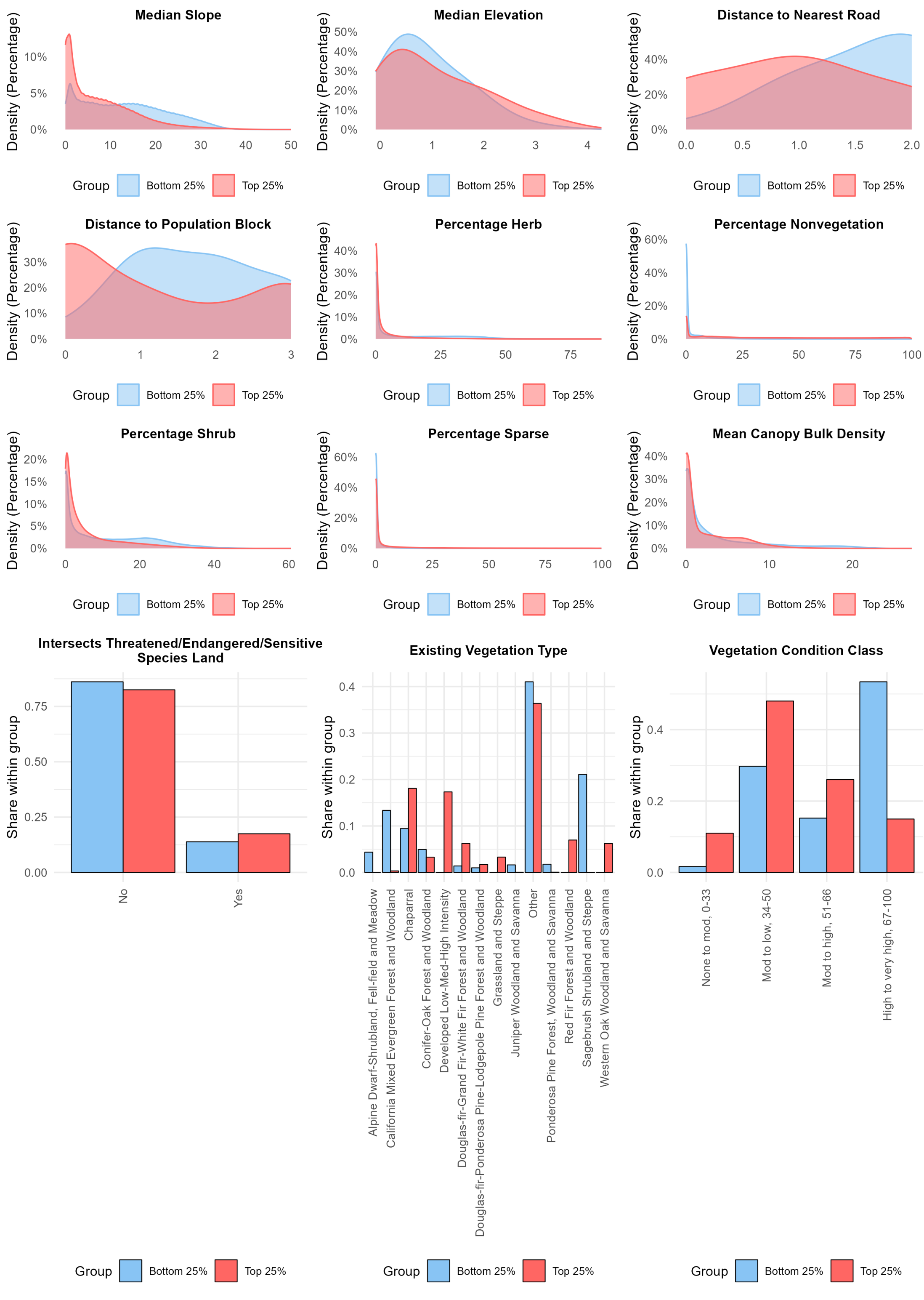
Note: Figure is based on a random 5 percent sample of cells displayed in Figure 2.

Figure A.2: Distributions of explanatory variables for pixels within the top and bottom quartiles of predicted cost per acre for mechanical thinning



Note: Figure is based on a random 5 percent sample of cells displayed in Figure 2.

Figure A.3: Distributions of explanatory variables for pixels within the top and bottom quartiles of predicted cost per acre for prescribed burn



Note: Figure is based on a random 5 percent sample of cells displayed in Figure 2.