Remotely Sensed Prescribed Fire Shrub Consumption in Mixed Conifer Forests from the Southern Sierra Nevada

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ABSTRACT

Live shrubs in forest understories pose a challenge for forest managers seeking to reduce fuel loads to mitigate wildfire risk with prescribed fire. Shrub consumption in prescribed burns is often highly variable and difficult to quantify, let alone explain the factors driving it. This study investigated spatial patterns and drivers of Sierra Nevada mixed conifer forest shrub consumption in prescribed burns through analysis of high-resolution imagery taken before and after prescribed fire. I applied a spatially explicit, generalized additive model to assess the importance of forest overstory and coarse woody debris as potential drivers of shrub consumption in prescribed burns. Shrub cover before burning was 37.5% in thin from below and 58.5% in the shelterwood treatments; post fire shrub cover was 35.9% and 32.6%, respectively. The patch density decreased for both treatments; shelterwood was not able to break up the larger patches of shrubs. The area weighted mean patch size increased for the thin from below and decreased for the shelterwood treatment. I found that coarse woody debris was a better driver of prescribed fire than proximity to overstory on the shrub canopies.

KEYWORDS:

Generalized additive model, High resolution imagery, Teakettle Experimental Forest, Mixed conifer

INTRODUCTION

Shrubs are an essential to ecosystem component of forested environments in the western United States and are important to wildlife, nutrient cycling, and biodiversity (Hunter 1990, White et al. 2015, North et al. 2016). However, shrubs can be strong competitors for soil moisture, which can limit tree establishment and growth (Fowells and Stark 1965, McDonald and Fiddler 1989). Disturbances that open forest canopies increase light on the forest floor, which can promote shrub establishment and growth. Furthermore, fire stimulates germination for several shrub species, which in combination with canopy disturbance, can lead to prolific shrub establishment and growth (Collins et al. 2019).

The use of prescribed fire to reduce fuel loads and mitigate wildfire risk has a long history in western North American forests, but long-term and large-scale implementation has yet to occur (Biswell 1989, Ryan et al. 2013, Pyne 2015). There are numerous studies that describe the ecological and wildfire hazard reduction impacts of prescribed fire in mixed conifer forests (e.g., Battaglia et al. 2008, Stephens et al. 2009, Fulé et al. 2012), but these tend to only capture relatively short-term dynamics following burns. There is some information on longer-term forest understory responses following prescribed fire (e.g., Webster and Halpern 2010), but similar information on fuel dynamics is comparatively lacking. This information can be particularly important in areas where prescribed fire facilitated major fuel changes (i.e. timber litter to shrub- or grass-dominated). While a transition to grass as the dominant fuel type may be relatively benign or beneficial from a wildfire hazard standpoint, a transition to a shrub fuel type can be problematic. Under wildfire conditions, shrubs can exacerbate surface fire intensity, as well as facilitate the movement of fire from the surface to the canopy. However, like other live fuels, shrubs can be challenging to burn in prescribed fire, which tend to be conducted in more mild conditions (Ottmar et al. 2016). Understand shrub consumption and responses under repeated prescribed fire will be important as the need for large-scale prescribed fire is increasingly recognized in western North American forests (USDA-USDI 2014, LHC 2018).

Although there is high variability of shrub consumption in prescribed fires, little effort has been made to quantify or explain this variability (Prichard et al. 2017). Live forest understory fuels have been generally overlooked in many prescribed fire studies (Agee and Skinner 2005). This study addresses this knowledge gap by not only describing the spatial patterns of shrub consumption during prescribed fire, but also to identify the factors associated with consumption. Specifically, I investigate how coarse woody debris and proximity to overstory trees related to the shrub consumption. Coarse woody debris can burn for long durations, which may release enough heat to allow for ignition and spread through live shrubs, even under prescribed fire conditions (Tappeiner et al. 2015). Proximity to conifer tree overstory may influence shrub consumption through deposition of needles and branches, which could provide enough low moisture content fuel to facilitate ignition and spread (Andreu et al. 2012). These objectives were investigated with an analysis of high-resolution imagery collected before and after prescribed fire within a long-term southern Sierra Nevada study area. I hypothesize that there will be an increase in heterogeneity and patchiness of shrubs prescribed fire and that there will be a strong correlation between the coarse woody debris and shrub consumption; less influential will be the proximity to overstory trees and their leaf litter that is deposited on the top of shrubs.

METHODS

Study site

The study area at the Teakettle Experimental Forest, located in the southern Sierra Nevada, 80 kilometers east of Fresno, California (North et al. 2002). Teakettle is a 1300-ha old-growth mixed conifer forest and is located at 36º 58' N and 119º 2' W with elevations varying from 2,000 to 2,800 m. Teakettle has a Mediterranean climate and receives an average of 134 cm of precipitation annually (Innes et al. 2006). The mixed conifer forests at Teakettle are composed of ponderosa pine (*Pinus ponderosa*), sugar pine (*Pinus lambertiana)*, incense-cedar (*Calocedrus decurrens)*, white fir (*Abies concolor)*, and black oak (*Quercus kellogii).* (North et al. 2002). Shrub species include mountain whitethorn (*Ceanothus cordulatus*), bush chinquapin (*Chrysolepis sempervirens*), pinemat manzanita (*Arctostaphylos nevadensis*), green leaf manzanita (*A. patula*), snowberry (*Symphoricarpos mollis*), sticky currant (*Ribes viscosissimum*), Sierra gooseberry (*R. roezlii*) and hazelnut (*Corylus cornuta*). Mountain whitethorn and bush chinquapin are the most abundant shrub species (North et al. 2002).

Figure 1. Teakettle on map of California. (Rambo et al. 2014)

Teakettle Experiment

The current Teakettle experiment began in 1998 and was designed to investigate the effects of thinning and prescribed burning on this forest. The study design is a randomized complete block design and each treatment unit (4ha in area) was randomly assigned a prescribed burn and thinning treatment (Table 1). There are three thinning treatments (understory, overstory, and control) and two prescribed fire treatments (burn and no burn). The understory thin was a thin from below that removed trees between 25-76cm and retained 40% canopy cover following Verner et al. (1992) guidelines. The overstory thin was a shelterwood treatment that removed trees greater than 25cm and kept 22 trees ha^{-1} with diameter at breast height (DBH) greater than 100cm. Thinnings occurred in 2001 and the prescribed fires in 2001 and 2017 (North et al. 2002).

Table 1: Treatments types at Teakettle Experimental Forest

	Thin from Below (unit)	**Shelterwood (unit)**	**No Thin (Control) (unit)**
Burn (unit)	3	3	3
No Burn (Control) (unit)	3	3	3

The understory thin was similar to a thin from below and followed the California Spotted Owl guidelines (CASPO), leaving 44 trees ha^{-1} with an average DBH of 91 cm (North et al. 2002). The overstory thin was similar to a shelterwood treatment, leaving 18 dominant trees ha^{-1} regularly spaced 20-25m apart (North et al. 2002).

The two experimental units from the Teakettle experiment were used for this study. One was a shelterwood and the other was a thin from below treatment. Both units were in high elevation mixed conifer forests that were dominated by white fir. Sites are also old growth forests that were never logged. Both areas are similar in aspect, slope and elevation. The thin from below treatment was at 2042m, 195 degrees azimuth, and 6-degree slope. It has a basal area of 22.85 m/ha and 42 percent of the unit is covered in shrubs. While the shelterwood treatment was at 2024m, 178 degrees azimuth, and 5-degree slope. It has a basal area of 28 m/ha and 24 percent of the unit is covered in shrubs.

The first prescribed fire occurred in 2001 and both units were burned on the same day. Mean temperature and relative humidity were 7.8 C and 66%, respectively. The thin from below treatment burned at slightly higher severity (defined by shrub consumption) than the shelterwood unit. The thin from below unit had 25% shrub cover before the burn and 23% after, while the shelterwood treatment had 42% shrub cover before the burn and 33% afterwards. Shrub consumption was estimated using remotely sensed data (information below).

Data Collection

The data was collected through remotely sensed imagery and stem maps (D. Krofcheck, *personal communication*). Imagery was collected using two drone flights, one before and one after the burns. A drone flew over the 4 ha units systematically before and after the prescribed fires. Over 100 images were stitched together to create an orthomosaic image (Krofcheck et al. 2019). Each image has ground resolution of just under 2cm/pix, ranging from 1.72cm/pix to 1.95cm/pix.

The Teakettle Experimental Research group provided geolocated stem maps of the trees in each 4 ha unit. The stem map includes information such as tree species, DBH, location, and mortality.

Spatial Pattern Analysis

To explore the spatial patterns of shrub cover in pre and post-burn conditions suitable class metrics from each raster image (resolution = .5m) were computed using the FRAGSTATS statistical package (McGarigal and Marks 1994). A total of 4 GeoTIFF raster files (2 "pre-burn" and 2 "post-burn") were imported into the software program and processed to calculate 3 class metrics. The configuration of the moving window used for the metric computation applied the 8-cell neighborhood rule for all the raster files, making results comparable. Among multiple class metrics, I selected a set of three metrics suitable to describe pattern change after fire in the study units: PD patch density (n° patch/100 ha), LPI largest patch index (%) and AREA_AM (area-weighted mean patch size m^2/sum of patch area).

Spatial Analysis

To determine if coarse woody debris and proximity to tree overstory increased shrub consumption during prescribed fire I used five layers in ArcMap: shrubs pre-burn, shrubs post-burn, shrubs-consumed, coarse woody debris pre-burn, and live canopy radius. Shrub consumption by fire was estimated by outlining the shrub canopies pre- and post-burn and then taking their difference. To access if coarse woody debris was important I outlined the exposed coarse woody debris pre-burn. Although this approach is biased because it is only outlining the coarse woody debris exposed from the shrub layer it is less biased than looking at the post-fire imagery which would lead to a confounding effect of only looking at coarse woody debris consumed in the fire. To access the impact of proximity of forest overstory on shrub consumption, canopy buffers from allometric equations using DBH and species information were obtained from a geolocated stem-map (Gill et al. 2000). This step assumes proximity to overstory occurs near or under trees.

To calculate the distance from the predictive variables in the burn, I rasterized all the shapefiles and reduced resolution to two meters. Then two new rasters were created: the distance from areas where fuel was consumed to live tree radius and the distance from burn to coarse woody debris. A data frame was created from the rasters including which unit the data came from, its location, if the pixel burned, and the distance of the pixel in the burn to the nearest log and nearest live radius. Figure 2 shows different raster layers used in this analysis. The last two raster layers are the distance from the burn to the predictive variables of logs and proximity to overstory.

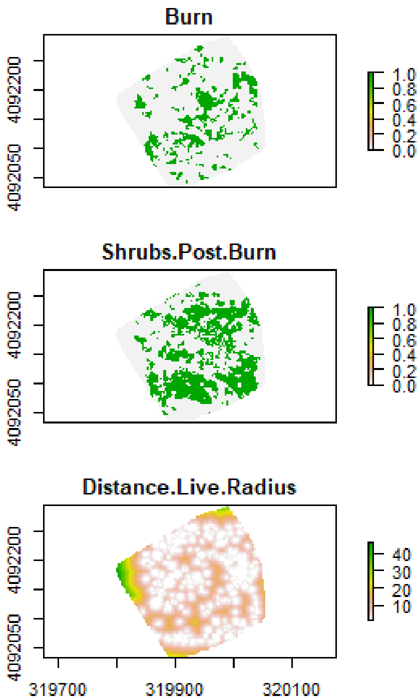

Figure 2. Rasters of GIS layers for input into the model

Statistical Analysis

I initially created a binomial generalized linear model (GLM) then created a Generalized Additive Model (GAM) to address some factors lacking from the initial GLM. The GLM had a logit link function to look at the trends of the variables in question. The equation I used is:

$$Y = \alpha + \beta_1 {*} CWD + \beta_2 {*} LR + \varepsilon \tag{1}$$

Where α is the y-intercept, β are the coefficients and CWD and LR represent distance to coarse woody debris and distance to live radius, respectively. The β_1 represents the predictive variable of logs and β_2 represents the predictive variable of live radius for proximity to overstory, and ε error distribution within the model. I used the logit link equation here to deal with the binary component of the outcome, because burn is binary. This equation identifies the basic trends of logs and canopy cover as predictive variables; however, it does not address spatial autocorrelation, and does not distinguish between the two units that burned. Spatial autocorrelation occurs when areas close to each other are not independent of one another (Tobler 1970). When models do not account for this, it can lead to autocorrelation in the residuals which violates the key assumption that residuals are independent and identically distributed (Anselin 2002). This causes spatial structuring in the response which can be seen in Figure B and Figure C in the appendix.

To address what was lacking the the GLM, I used a Generalized Additive Model (GAM). Similar to the GLM, the GAM is a multiple regression model; however, it differs from the GLM in that is has at least one smoothing function in the predictor function and has the advantage that predictor variables have nonlinear effects on the response variables. Its linear regression is replaced by splines, non-parametric functional curves with multiple parameters, making it really good at representing nonlinear responses (Zuur et al. 2009). The smooth function that was added to the GAM was s(X,Y), while distance to CWD, LR, unit, α, and ε are fixed variables. The equation being:

$$Pr(Burn) = \alpha + \beta_1 Unit + \beta_2 f(CWD) + \beta_3 f(LR) + s(X, Y) + \varepsilon \qquad (2)$$

To address the issue of spatial autocorrelation, the geographic location of the pixels was fixed using splines. Though this does not address the issue of spatial autocorrelation directly, it accounts for the trends in the data (Cressie 1993). I used model selection to determine which model is best fitting model. Akaike's information criteria (AIC) (Eilers and Marx 1996) were used to determine this by looking at the optimal set of explanatory variables. To do this, I ran the model with different fits of CWD and LR including, linear, exponential, and logistical. The model with the smallest AIC determined as the optimal model.

RESULTS

In my spatial analysis, I found that the prescribed fire in the different treatments burned the shrub patches differently. In my statistical analysis, I fit a generalized additive model to the data to best describe the relationship between the predictive factors of shrub consumption and the probability of the burn.

Spatial Analysis

To understand how the shrub spatial pattern changed, I computed class metrics from pre-burn and postburn GeoTIFF rasters through Fragstats.

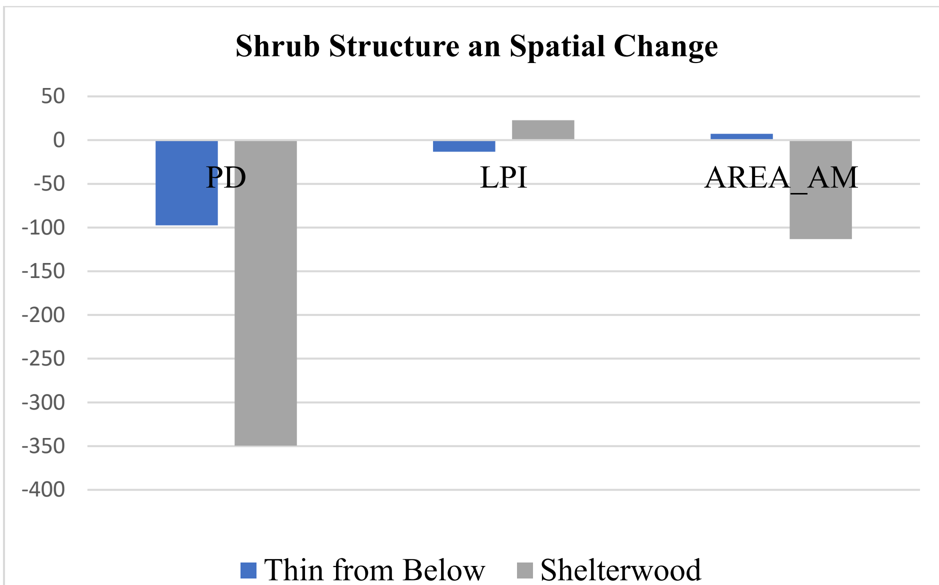

Figure 3. Shrub Pattern Change in the two different-treatments units. This graph depicts the percentage change ((postfire index - prefire index)/prefire index)*100) in shrub patch characteristics. Where PD represents patch density. LPI represents the largest patch index. AREA_MN is the area-weighted mean patch size.

The Fragstat analysis was done in the class level to understand the changes in patterns of the different patches of shrubs. It showed that for both units, the patch density decreased. Patch density is the number of patches divided by the whole area and is in the units of patches/100 ha (McGarigal and Marks 1995). More notably, the largest patch index, which is the percentage of the area comprising the total patch (McGarigal and Marks 1995), increased for shelterwood and decreased for thin from below. As for the area-weighted mean patch size, the thin from below had a slight increase and the shelterwood had a large decrease. The area-weighted mean patch size gives a meaningful perspective on landscape structure by weighting the larger patches more heavily than the simple area mean (Turner and Gardner 2015). This helps give a better understanding of how the fire behaved across the landscape and how and which shrubs it consumed.

Table 2. Unit Characteristics. The percentage of cover of shrubs before and after the prescribed fire, as well as the canopy cover of both experimental unit.

Unit	Shrub Cover	Shrub Cover Post Fire	Canopy Cover
Thin from Below	37.5%	35.9%	17.6%
Shelterwood	58.5%	32.6%	18.7%

Statistical Analysis

To create a statistical model that has the best fit I created a GAM with the equation:

$$\Pr(\text{Burn}) = \alpha + \beta_1\text{Unit} + \beta_2 e^{-\text{CWD}} + \beta_3\text{LR} + s(X, Y) + \varepsilon \tag{3}$$

Where α is the y-intercept, β are the coefficients and x is the distance of the predictive variables. The model with the best fit had an adjusted r-squared of .724 and an AIC of 5202.853 as seen in Table A1. The model had a power of 73.2%. The model with the best fit has a logarithmic relationship to coarse woody debris, and a linear relationship for the proximity to overstory. There was one other model that had a similar AIC of 5204.029, this had coarse woody debris and proximity to overstory as negative exponential.

Table 3. GAM Regression Output. Information from the GAM

	Regression coefficient	**Standard Error**	**P-values**
Intercept	2.492e10^9	1.195*10^10	.835
Unit	-1.98*10^10	2.89*10^10	.493
exp (-CWD)	7.018	2.271	.002
LR	9.208*10^-2	2.883*10^-2	.118

As seen in Table 3, distance to CWD is the only significant variable. The regression coefficients for CWD represents the probability of burn given the proximity to coarse woody debris. There is a negative relationship between burn and distance to CWD. LR regression coefficient represents the probability of burn given the proximity to overstory. Here, the relationship between LR and distance is positive. The regression coefficient for Unit, creates an offset that accounts for the difference in probability of burn between the different experimental units. The regression coefficients for proximity to overstory and proximity to coarse woody debris have very different magnitudes. Though both variables have different fits, coarse woody debris has a negative exponential fit and a regression coefficient much larger than proximity to overstory which has a linear fit and a much smaller regression coefficient.

Table 4. Sensitivity Analysis of Regression Coefficients

<table>
<tr><th>Distance</th><th>β_2</th><th>e^{-CWD}</th><th>$\beta_2 * e^{-CWD}$</th><th>Δ_1</th><th>β_3</th><th>LR</th><th>$\beta_3 * LR$</th><th>Δ_2</th></tr>
<tr><td>4</td><td>7.018</td><td>0.018</td><td>0.129</td><td rowspan="2">-0.082</td><td>0.009</td><td>4</td><td>0.037</td><td rowspan="2">0.01</td></tr>
<tr><td>5</td><td>7.018</td><td>0.007</td><td>0.047</td><td>0.009</td><td>5</td><td>0.047</td></tr>
<tr><td>9</td><td>7.018</td><td>4.54×10^{-5}</td><td>0.0003</td><td rowspan="2">0.0005</td><td>0.009</td><td>9</td><td>0.083</td><td rowspan="2">0.009</td></tr>
<tr><td>10</td><td>7.018</td><td>0.0001</td><td>0.0008</td><td>0.009</td><td>10</td><td>0.092</td></tr>
</table>

In a sensitivity analysis that accounted for the different relationships of the different predictive variables, when the proximity to burn is close, the coarse woody debris is more sensitive. However, when distance from the burn increased, the sensitivity to the coarse woody debris decreased.

Proximity to Overstory

As seen in figure 4, the GAM shows that, at least for the thin from below, the further from the tree canopy, there is a decrease in the probability of the shrubs being consumed. Figure 5 shows the shelterwood unit shows a less clear relationship; perhaps, because of the inherit structures of the units.

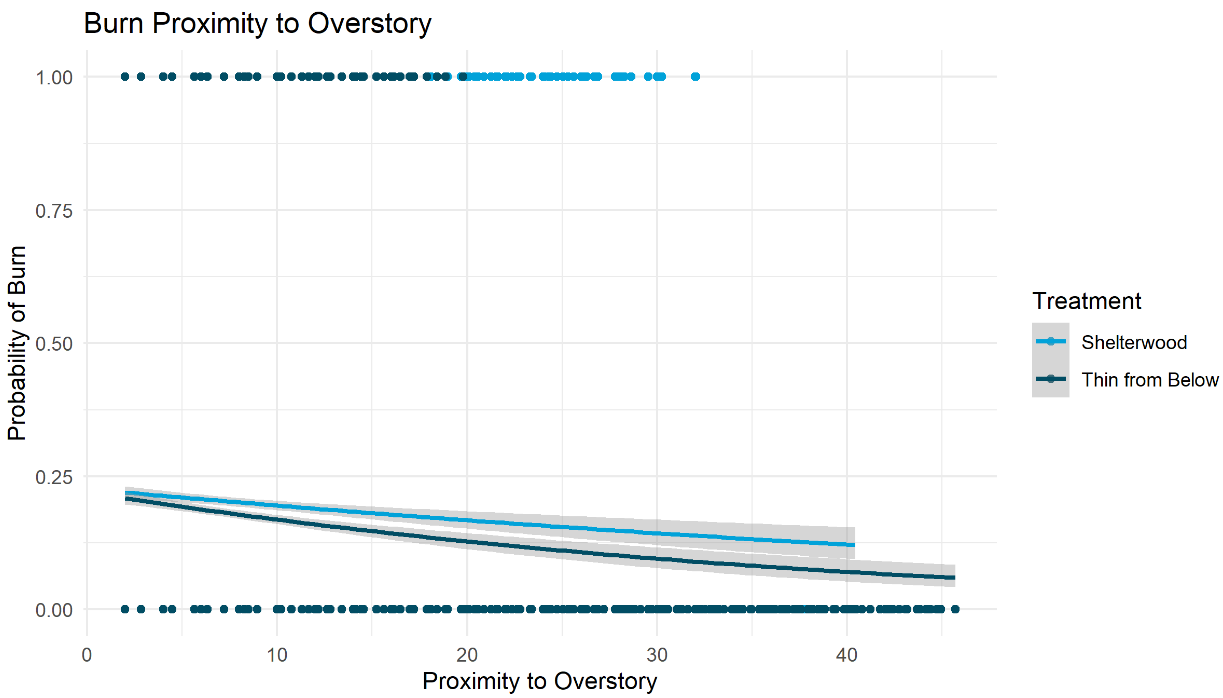

Figure 4. Relationship Between Probability of Burn and Proximity to Overstory.

The predictive variable of proximity to overstory did not have as strong of a relationship as the coarse woody debris as seen in the residuals graph. But the best iteration of the model was when the proximity to overstory factor was depicted as linear.

Coarse Woody Debris

As seen in Figure 5, the GAM shows that for both units, the further from the coarse woody debris, the less likely the shrubs are to burn. The slight difference in the shape of the functions may have to do with the variations with the shrub structure.

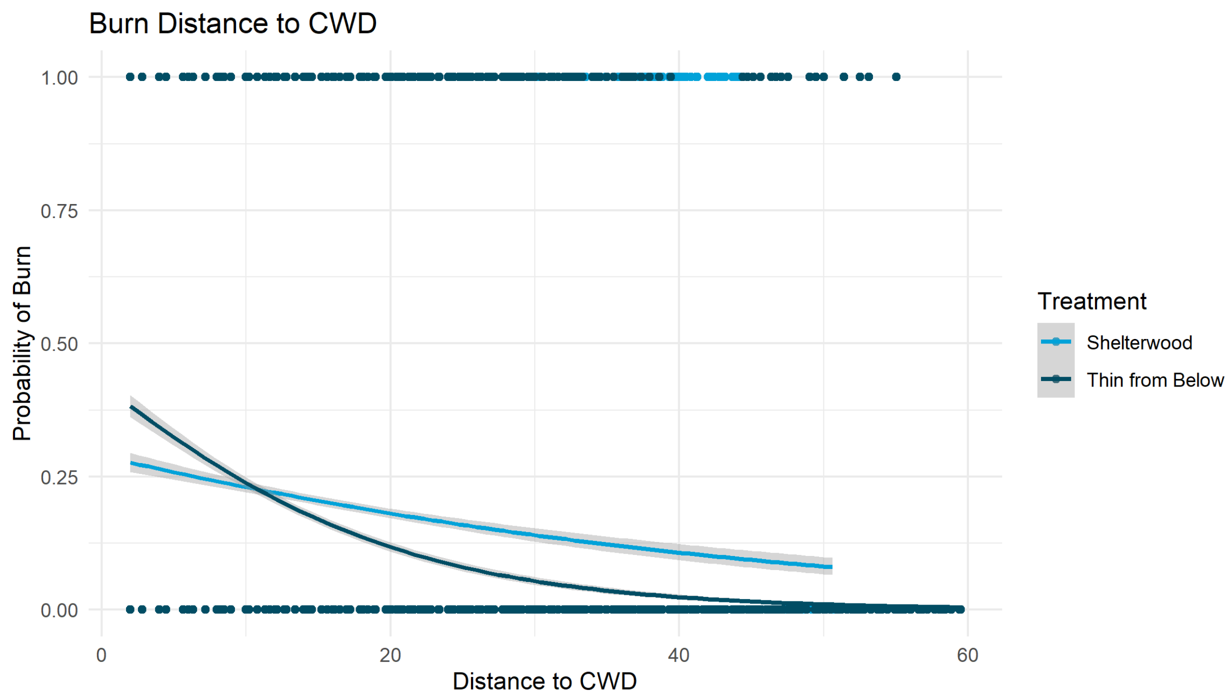

Figure 5. Relationship Between Probability of Burn and Distance to Coarse Woody Debris.

The overall relationship of coarse woody debris to shrub consumption was modeled as a negative exponential.

DISCUSSION

Quantifying shrub consumption in a prescribed fire within a long-term study, with multiple reburns, is important for reducing fuel loads and mitigating wildfire risk (Biswell 1989, Ryan et al. 2013, Pyne et al. 2013). Shrub consumption in prescribed fire can be highly variable (Prichard et al. 2017). I assessed the spatial patterns of shrubs consumption as well as factors that correlated with their consumption. Spatial structure of the shrubs became more heterogeneous and patchy due to the prescribed fire. The results showed the only significant predictive factor was coarse woody debris.

Spatial Analyses

The prescribed fire created structural changes in the shrubs and varied in consumption patterns across the two sites. Though both had a decrease in patch density, they differed in their LPI and the weighted area mean. The increase in patches means that there was an increase in heterogeneity, but ultimately the burn created different patterns. This could potentially be due to the previous silvicultural treatments enacted in these areas, creating different structures within the unit.

The shelterwood had more open areas that allowed for more shrubs to grow in a contiguous, homogenous patch. The larger patches made it harder for the fire to penetrate and break up these areas. Thus, for the shelterwood treatment, the LPI increased. In contrast, the thin from below treatment had less large open spaces, thus the shrub patches were originally less contiguous, making it easier for the LPI to decrease.

The shelterwood unit more shrubs were consumed; however, the largest and most contiguous areas were unable to burn. In the thin from below unit, there was less shrub consumption, but what did burn led to a more heterogeneous and less contiguous shrubscape.

Statistical Analyses

To understand the drivers of the shrub consumption I created a statistical model using coarse woody debris and proximity to overstory as explanatory variables. I found that coarse woody debris was the stronger predictor of shrub consumption. This is consistent with other studies (Cansler et al 2019) that found large woody debris increases the fire intensity and spread. The coarse woody debris creates a jackpot of fuel that increases intensity (Cansler et al. 2019) leading to higher fuel consumption.

Proximity to overstory was statistically insignificant, though it showed that shrubs closer to the overstory were less likely to burn. The lack of significance could be because of several factors. My analysis assumed shrubs closest to the overstory would have higher amounts of needle drape. Using proximity to overstory without differentiating between species may have limited the effectiveness of this analysis. Needle drape is far more likely to occur from pine than firs due to the structure of the needles (Fonda et al. 1998). Also, proximity to canopy cover does not account for wind dispersing needles. Lastly, there is the limiting effect of the remotely sensed imagery. Shrubs shaded out by the tree canopy, forms a less continuous shrub fuel layer; however, I was unable to see that with the remotely sensed imagery. The microclimates associated with the shading of the canopy, increases the moisture content of those shrubs. Ultimately, more ground data needs to be collected pre and post fire to understand these limitations.

Management Implications and Conclusions

These findings are important from a managerial point of view. Different silvicultural methods such as shelterwood and silvicultural treatments that open up the canopy increase the light availability and thus increase the potential for shrubs to grow. Also, prescribed fires have been shown to increase shrub presence due to the activation of shrub bank and resprouting (Collins et al. 2019). This was seen in 2001 when, after a history of exclusion occurred, a prescribed fire was implemented on this land, causing a large increase in abundance of shrubs (North et al. 2007). By understanding what causes the shrubs to be consumed as well as in what pattern, may help managers more effectively implement prescribed fires, or implement harvest plans that lead to more effective shrub consumption once the prescribed fire is implemented.

This study had some limiting factors that I hope to address in future iterations of the study. For instance, there was no ground truthing model to compare the remote sensing model to. Also, the model does not account for all potential factors influencing shrub consumption, nor would it be possible to do so; however, I hope to add in more factors in the future looking at topographic position index as well as climate because both climate and topography are very important to fire behavior. Another limiting factor is, this is a case study that is spatially explicit, the legacy of the management as well as the vegetation type, affect the burn, making the finding somewhat difficult to extrapolate into larger or different areas.

Understanding how prescribed fires affect the understory and particularly shrubs is very important to managers as it can reduce costs and be used in areas where mechanical treatments are impossible. Prescribed fires can be cheaper than mechanical treatments making it a better option for pace and scale. Also, prescribed fire can be used where mechanical treatments are prohibited such as wilderness environments and steep slopes.

ACKNOWLEDGEMENTS

My advisors Dr. Brandon Collins and Dr. Scott Stephens for the continuous support and guidance. Thank you to the amazing teaching staff of ESPM 175, Dr. Samuel Evans, Dr. Patina Mendez for their feedbacks, edits, enthusiasm, and guidance, as well as helping construct an organized way to create a thesis in manageable pieces. Jacob Levine, for his patience in teaching me statistics and guiding me through the statistical models and analysis; as well as all of his support through my different analysis and encouragement to apply and present my thesis at AFE last fall. Dr. Francesco Malandra teaching me Fragstats and helping the spatial analysis. Hudson Northrop, working on the geospatial analysis. Dr. Dan Krofcheck, former post doc of the Hureau Lab of University of New Mexico, for supplying the imagery. Marissa Goodwin, Research Scientist at the University of New Mexico, for providing information on the prescribed fire and field data. The peer editing and continuous support from my thesis working group: Celia Rodriguez, Augustus Clements, and Ursula Hardwood.

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APPENDIX

Table A. GAM iterations. These are the different model iterations I tried for the different functions of the predictive variables, while keeping the number of points and knots constant.

GAM Functions	AIC
burn ~ Unit + CWD + LR	5213.618
burn ~ Unit + CWD^2 + LR	5213.618
burn ~ Unit + CWDs^3 + LR	5213.618
burn ~ Unit + CWD + LR^2	5213.618
burn ~ Unit + CWD + LR^3	5213.618
burn ~ Unit + CWD^2 + LR^2	5213.618
burn ~ Unit + CWD^3 + LR^3	5213.618
burn ~ Unit + exp(-CWD) + exp(-LR)	5204.029
burn ~ Unit + exp(-CWD) + LR	5202.853
burn ~ Unit + CWD + exp-(LR)	5214.728

For each GAM, there were 5000 points and 500 knots.

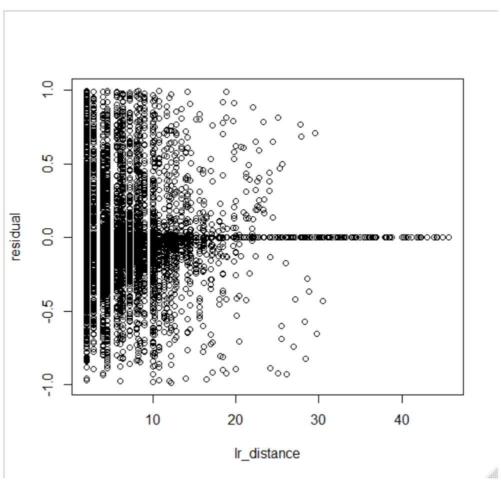

Figure B. Residuals of Proximity to Overstory in Model. Unit of the residuals of proximity to overstory from the statistical model.

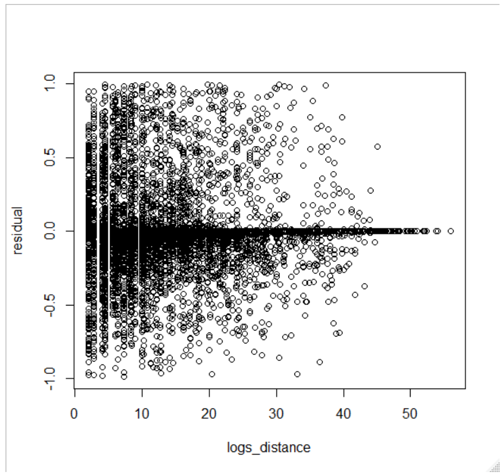

Figure C. Residual of Coarse Woody Debris. Unit of the residuals of coarse woody debris from the statistical model.