Long-term trajectories of fuel and stand structure in experimentally-treated dry forests of central Washington

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Abstract

Severe wildfires are becoming more common in dry forests of western North America. Fuel treatments including forest thinning and prescribed burning are crucial tools for helping forest managers reach forest restoration and human community protection goals. However, longterm fuel, stand structure, and potential wildfire response to fuel treatments has not been as well studied as short-term response. To address this research gap, I explored 13-18 year ('longterm') responses to control, thinning, burning, and thinning plus burning treatments Mission Creek Fire and Fire Surrogates site in central Washington. I conducted nonmetric multidimensional scaling (NMDS) analyses to assess balance and variation in multivariate space in the pretreatment sample period, and movement from the pretreatment to the longterm sample period. I conducted multiple cluster analyses to explore possible groupings of replicate units before and after treatment. Finally, I conducted principal components analyses (PCA) to assess possibilities for variable reduction. NMDS suggests reasonable experimental balance before treatment, and minor treatment-level effects of treatment with inconsistent plot-level effects. Cluster analysis weakly suggests some clustering in western and eastern replicate units, and some erosion of this clustering after treatment. PCA suggests that modelled response variables are more correlated than field-collected response variables, and that modelled tree mortality has the greatest relationship to overall variance in the dataset. These results are considered exploratory analyses, and will be complimentary to hypothesis testing analyses I am also conducting.

Introduction

    Severe wildfire is increasing in dry forests of western North America, often threatening forest persistence (Coop et al. 2020) and human community stability (Radeloff et al. 2018). Climate change, expanding human development, and fire suppression are contributing to the increasing trend in severe wildfire (Hessburg et al. 2021). Fire suppression and exclusion of Indigenous fire in dry forests has led to uncharacteristic stand conditions, including increased fuel load and continuity, relative to pre-colonization levels (Hagmann et al. 2021). Therefore, fuel treatments are considered an integral tool for of dry forest restoration planning (Franklin and Johnson 2012). Fuel treatments can also be effective at reducing wildfire severity in a wide range of weather conditions, particularly treatments that include prescribed burning, when wildfire occurs less than ten years following treatment (Prichard et al. 2021).

    Although the short-term effects of fuel treatments on fuel loads are well studied, the longer-term (> 5 years) dynamics of fuel treatments are not well understood. Most studies that have empirically addressed long-term fuel and stand structure dynamics on the stand scale have found that most variables are statistically indistinguishable from controls and/or pretreatment values, with high variability within and among treatment units (Battaglia et al. 2008, Chiono et al. 2012, Stephens et al. 2012, van Mantgem et al. 2016, Crotteau et al. 2018, Hood et al. 2020, Morici and Bailey 2021). Tree density and canopy fuel loads, however, likely remain below pretreatment levels into longer term study periods in thin and thin plus burn treatments. In stands receiving a thin or thin plus burn treatment, recruitment of ladder fuels, those fuels that connect surface and canopy fuels, appears to be a key process driving modelled wildfire severity (Stephens et al. 2012, Hood et al. 2020). In experiments, control units have sometimes shown

similar temporal dynamics to treated units for some variables, decreasing estimates of the effect of treatment (Stephens et al. 2012, Hood et al. 2020, Morici and Bailey 2021).

High within- and among-stand variability in treatment units (Stephens et al. 2012, Hood et al. 2020, Morici and Bailey 2021) suggests that factors other than treatment category influence fine-scale fuel dynamics and fuel treatment longevity. These factors might include pretreatment condition, treatment intensity, and site productivity (Jain et al. 2012). Variance within treatment categories is important for managers to consider (Jain et al. 2012), and it may confound or weaken the power of categorical statistical tests used in many fuel treatment studies. Multivariate techniques such as ordination and cluster analysis afford succinct exploration of variance patterns within- and among- treatment units with complex datasets (Legendre and Legendre 2012). Therefore, multivariate techniques may be useful in studies focused fuel and fire behavior, which are characterized by high variance and large number of response variables (Reinhardt et al. 2008, Keane et al. 2012).

In this study, I will explore plot-scale long-term (~15-year posttreatment) fuel, stand structure, and modelled fire behavior responses to control, burn, thin, and thinburn treatments. All analyses in this paper will be considered exploratory analyses, because I'm conducting hypothesis testing with methods outside the scope of class. I will use field data I collected at the Northeastern Cascades site of the nationwide Fire and Fire Surrogates study. Earlier publications focused on fuel, stand structure, and modelled fire behavior responses have found high within- and among- stand variance (Agee and Lolley 2006). Specifically, I will ask the questions, and have the following hypotheses:

Question 1: *Do plots within different treatment categories show similar patterns within multivariate space during the pretreatment sampling period, and do they appear to respond consistently to treatment in the longterm?*

Question 2: *Do plots within a replicate unit and within spatially proximate replicate units will group together in multivariate space in the pretreatment sampling period, and do different replicate units within a treatment category group together after treatment?*

Question 3: *Could the number of variables needed in analysis potentially be reduced by data reduction methods?*

Hypothesis 1: Plots within treatment categories will show incomplete overlap in ordination space. They will respond in a consistent direction to treatment.

Hypothesis 2: Plots within a replicate unit and spatially proximate plots will largely group together in the pretreatment period, and treatment will cause more intermixing of spatially distant units within the same treatment category, although this relationship won't be perfect.

Hypothesis 3: There is likely to be correlation in variables that will allow for data reduction, particularly because the modelled fire behavior variables depend directly on the field measured data.

Methods

Study Area

The Northeastern Cascades site of the Fire and Fire Surrogates study is in central Washington State, south of Cashmere. The area was selected to characterize dry forests of the interior Columbia River basin (Agee and Lehmkuhl 2009). These forests occupy relatively low elevations, and the tree layer is dominated by ponderosa pine (*Pinus ponderosa*) and Douglas fir (*Pseudotsuga menziesii*), with smaller components of western larch (*Larix occidentalis*) and grand fir (*Abies grandis*) (Rossman et al. 2020). The precolonial fire return interval was 6 to 21 years (Agee and Lehmkuhl 2009). Since the 1930s, however, fire-suppression and removal of Native Americans from the landscape has resulted in a buildup of fuels and increase of shade-tolerant, fire-intolerant tree species (Hessburg and Agee 2003). Today, structure and composition is highly affected by site moisture, which is largely driven by topography (Agee and Lehmkuhl 2009).

Treatment selection and implementation

The study was designed to experimentally test the effects of four treatments: control, burn, thin, and thin plus burn. In the late 1990s, researchers randomly chose 12 experimental units of ten hectares or larger, from a field of 30 potential units. Within the 12 chosen units, researchers randomly assigned three replicates for each of four treatments. Four units were changed from their initial assignment due to operator concerns about logistics and safety of prescribed burning, given proximity to structures for two of the units. Units were chosen to be roughly rectangular in shape, 90% forested, with slopes averaging less than 50%, and primarily consisting of the *Pseudotsuga menziesii* series of Lillybridge et al. (1995). Thinning projects

were implemented in 2002 or 2003, and burning projects were delayed to 2004 or 2006 due to

weather. 2004 burns were of lower intensity and severity than prescribed, while 2006 burns met

management goals. In 2012, a wildfire (the Poison Fire) burned four replicates: two controls,

one thin, and one burn unit. The long-term experimental balance therefore consists of three

thinburn units, two thin units, two burn units, and one control unit (figure 1) (Agee and

Lehmkuhl 2009).

Data collection

In 2019 and 2020, I led field crews resampling fuel plots. We sampled 204 plots: 66 thin

plus burn plots from three units, 58 burn plots from two units, 55 thin plots from 2 units, and 25

control plots from one unit. The protocols below match those followed in pretreatment and

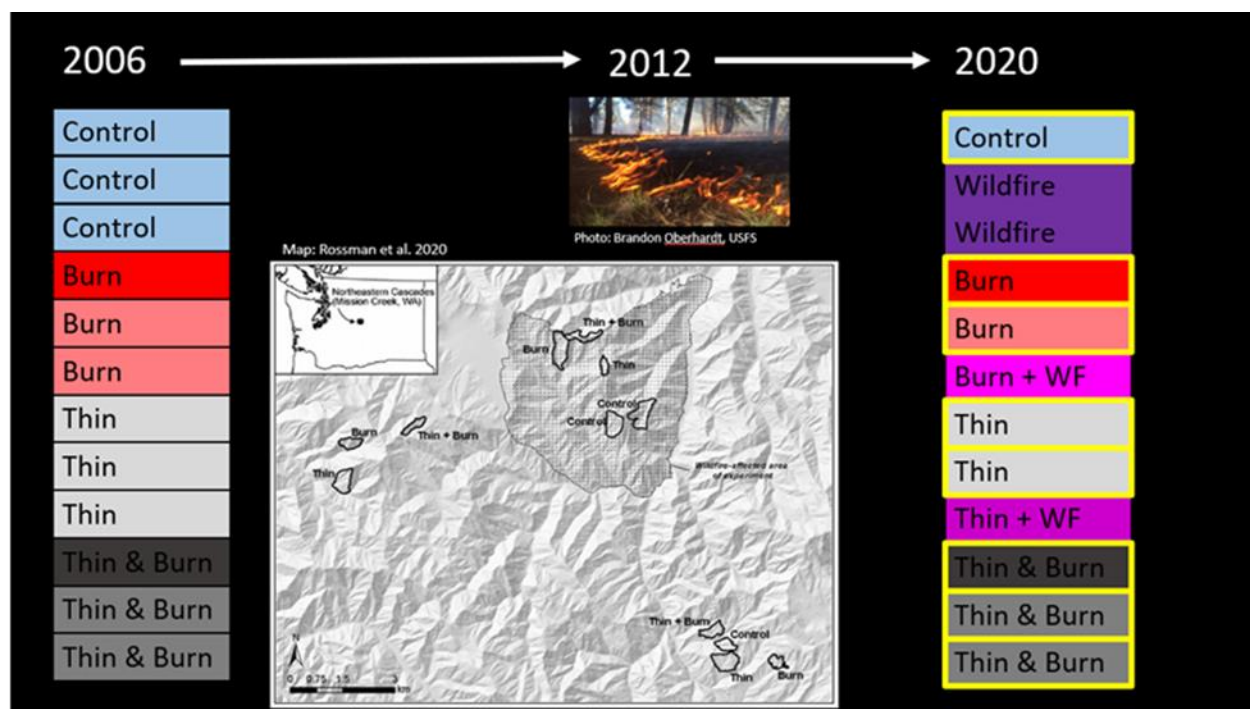short-term surveys (Agee and Lolley 2006, Agee and Lehmkuhl 2009), except where noted.

Figure 1: Experimental balance at the Mission Creek site, before and after the 2012 Poison Fire burned three of the replicate units.

Northeastern Cascades Fire and Fire Surrogates
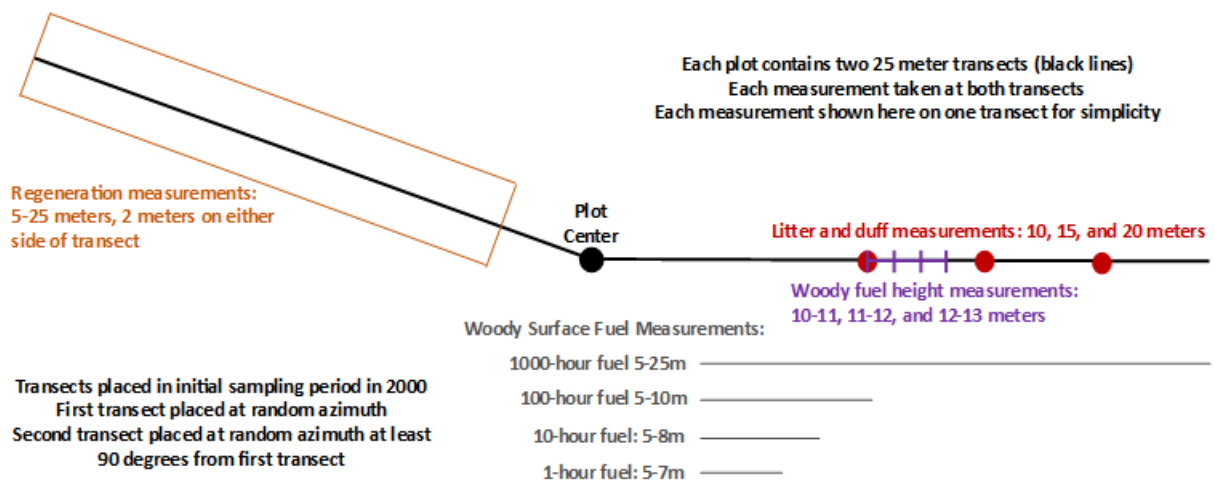## 2019 and 2020 Transect Measurements

Each plot contains two 25 meter transects (black lines)
Each measurement taken at both transects
Each measurement shown here on one transect for simplicity

Regeneration measurements:
5-25 meters, 2 meters on either
side of transect

Plot
Center

Litter and duff measurements: 10, 15, and 20 meters

Woody fuel height measurements:
10-11, 11-12, and 12-13 meters

Woody Surface Fuel Measurements:

1000-hour fuel 5-25m

100-hour fuel 5-10m

10-hour fuel: 5-8m

1-hour fuel: 5-7m

Transects placed in initial sampling period in 2000
First transect placed at random azimuth
Second transect placed at random azimuth at least
90 degrees from first transect

Figure 2: Fuel variable sampling design

We measured vegetation structure and fuel profiles following standard approaches. At each plot we measured trees, shrub and herb fuels, fuel model (Anderson 1982), and canopy cover in a circular plot, and surface fuels in two Brown's transects (Brown 1971). In each transect, we counted one-hour fuels for two meters, ten-hour fuels for three meters, hundred-hour fuels for five meters, and thousand-hour fuels for twenty meters. For thousand-hour fuels, diameter, decay class, and species were also recorded. Additionally, we measured litter depth, duff depth, and woody fuel height at three points per transect (figure 2). We estimated coverage of fuel models over the same plot, using Northern Forest Fire Lab (NFFL) models (Anderson 1982). Canopy cover was measured with densiometer readings facing each of the four cardinal directions from plot center.

Due to variable tree density, we used an adjustable radius design to determine tree plot size. We used two radii per tree plot: one for 'small trees' ($\leq$0.1 cm diameter at breast height [dbh] to >30 cm dbh), and one for 'large trees' ($\leq$30 cm dbh), to avoid clumps sapling causing undersampling of larger, fire resistant trees. We customized at each plot to sample at least ten

trees per plot, at least five of which had to be large trees. The maximum allowable plot radius

was 18 meters. Radii were adjustable in meter increments. The small tree radius could be

smaller than or equal to the large tree radius, but not larger. For each tree, we recorded species,

dbh, total height, height to base of live crown, height to base of dead crown, char height, char

circumference, likely cause of death if applicable, and mistletoe presence. The protocol for

determining tree plot size was different than pretreatment surveys, which used variable

rectangular plots with coarser size increments, and short-term surveys, which used cruising

prisms. The individual tree measurements were the same (Agee and Lolley 2006, Agee and

Lehmkuhl 2009).

Fire modelling

I used the Forest Vegetation Simulator Fire and Fuels Extension (FVS-FFE) (Reinhardt

and Crookston 2003) to model fire behavior metrics and canopy fuel loads, and the First Order

Fire Effects Modelling program (FOFEM) (Reinhardt et al. 1997) to model potential tree

mortality in a wildfire. All fire and mortality modelling was done on the plot level, to allow

assessment of variability in response within replicate units and treatment categories. Fuel

moisture and weather parameters were gathered in Fire Family Plus (Bradshaw and McCormick

2000), and reflect 80th percentile fire weather conditions for the fire seasons (June 15 –

September 15) of 2002 through 2017, for two Remote Automatic Weather Stations near the

Mission Creek Site (Swauk and Dry Creek). I input measured surface fuel loads into FVS-FFE.

I allowed FVS-FFE to choose the fuel model based on stand structural data, because of suspected

differences in fuel model assignments between the pretreatment and longterm field crews. The

surface flame height from FVS-FFE was input into FOFEM along with tree species, diameter,

height, and canopy base height information, to model tree mortality by basal area and by density. The FVS-FFE and FOFEM model outputs were added to the field collected fuel and stand structure data, to serve as response variables in multivariate analyses (see metadata for full list of response variables).

Statistical methods

      All data manipulation and analyses were conducted with the R statistical software, version 4.1.2. For all analyses, all variables were relativized by maximum to account for the different units and scales of measurement of the response variables, which were all on continuous and positive (or 0) scales. The pretreatment and longterm data were relativized together, so that relativized variables would have the same meaning in absolute terms for both the pretreatment and longterm sampling periods. This will not affect patterns within a single response variable within a given sample period, but may have affected the relationships among different response variables within a sampling period.

      I used nonmetric multi-dimensional scaling (NMDS) to assess within- and among-treatment variation in multivariate space, and the effects of treatment on multivariate patterns. My NMDS used a Euclidean distance matrix, because all response variables are continuous and symmetric (shared absences are likely to be meaningful). I ran separate NMDS for the two sample periods. Trial and error showed three axes to be sufficient to reach an acceptable stress value; the pretreatment NMDS would not converge with two axes. I assessed multivariate patterns by coloring by treatment, and by plotting species scores onto the ordination. I assessed change by plotting treatment centroids of both time periods, and by running a Procrustes analysis on the difference between the ordinations of the two time periods.

I used cluster analyses to assess grouping patterns of plots in relation to replicate unit and spatial distribution. The Mission Creek study contains eight replicate units, so initially I divided cluster analysis results into eight groups. To assess the degree of consistency between different clustering methods, I used seven different techniques to check for consistency between groupings: hierarchical polythetic agglomerative clustering with five different cluster linkage methods (single linkage, complete linkage, centroid linkage, average linkage, and Ward's method), as well as two different non-hierarchical k-means methods (using function stats::kmeans() in and cluster::pam() with Euclidean distance). To visualize the groupings, I produced confusion matrices, which represented what proportion of plots within a given replicate unit (column) fell within a given cluster analysis group (row). To assess changes between sampling periods, I compared these confusion matrices for the pretreatment sample period and the longterm sample period. After the initial analysis weakly suggested the possibility of two distinct geographical clusters of replicate units, I reran all cluster analyses with two clusters and two groups of units *a posteriori*,

I used principal components analysis (PCA) to assess possibilities for response variable reduction. I used response variables from both sample periods in a single ordination, because the goal of the PCA was to assess relationships among variables, not to assess temporal patterns in ordination space as I did with the NMDS. I attempted log, square root, and/or squared transformations of some response variables, as there are both right and left skewed distributions. However, these transformations often produced distributions that were skewed and/or discontinuous, appearing farther from normality assumptions than the untransformed distributions. Therefore, I elected not to transform any response variables, and the results must be taken with caution due to some violation of normality assumptions. For interpretation, I

plotted the loadings of the first three principal components, and created a table listing all

response variables that displayed a correlation stronger than 0.3 or -0.3 with one of the first three

principle components. Additionally, I conducted separate PCAs for field measured variables and

modelled variables, and plotted the loadings of these two PCAs to see if separate patterns would

emerge.

Results

Question 1: *Do plots within different treatment categories show similar patterns within*

multivariate space during the pretreatment sampling period, and do they appear to respond

consistently to treatment in the longterm?

The NMDS plots (figure 3) suggested that treatment categories have substantial overlap

in multivariate space during the pretreatment period. The pretreatment ordination suggested a

relationship between sample size and variation in ordination space; the control treatment shows

the smallest convex hull, and had just one replicate unit, while the thin plus burn treatment shows

the largest convex hull, and had three replicate units. The burn and the thin treatments, each with

two replicate units, showed intermediate sized hulls. The centroids of the burn, thin, and thin

plus burn treatments were close to one another, while the control centroid had a slightly higher

axis one score, corresponding with more open stand structure and less fuel. The longterm

ordination showed qualitatively similar patterns of variance and similar locations of response

variable scores. The control and thin plus burn treatments showed the greatest movement of

centroids from pretreatment to longterm sample periods, with control moving towards more

closed canopy later successional conditions, and thin plus burn moving towards more open

conditions. Procrustes analysis (figure 4) suggested that individual plots changed in a highly
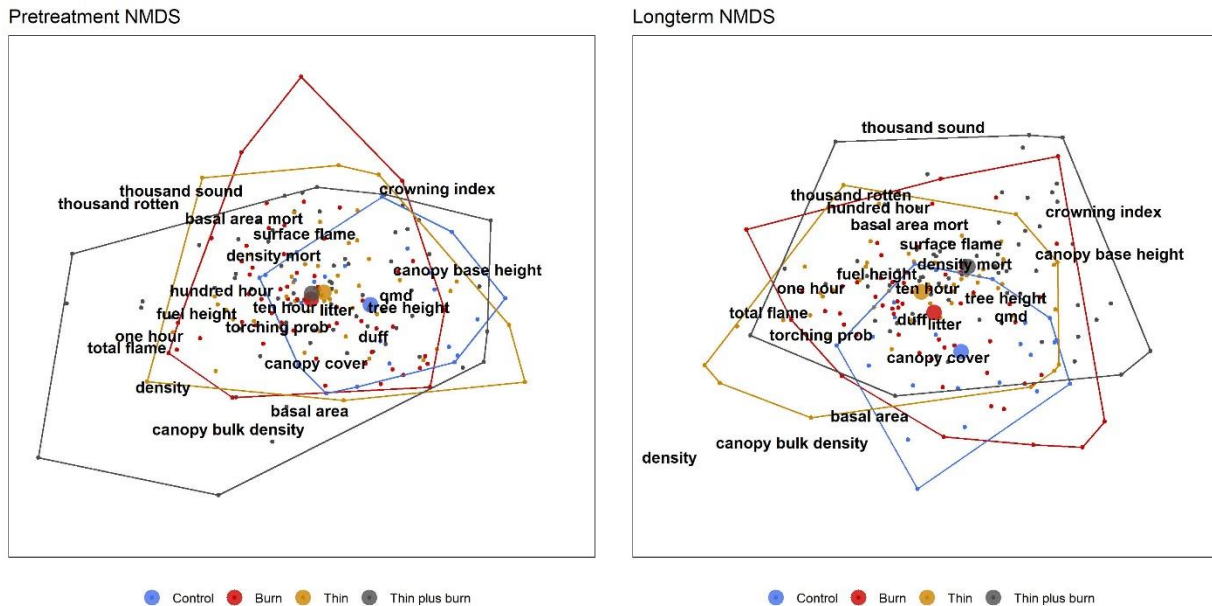
variable

Figure 3: NMDS graphs of the pretreatment and longterm sampling periods, colored by treatment. Large points are centroids, small points are plots. Both ordinations were run with three axes. The pretreatment NMDS had a stress of 0.10, and the longterm 0.11.
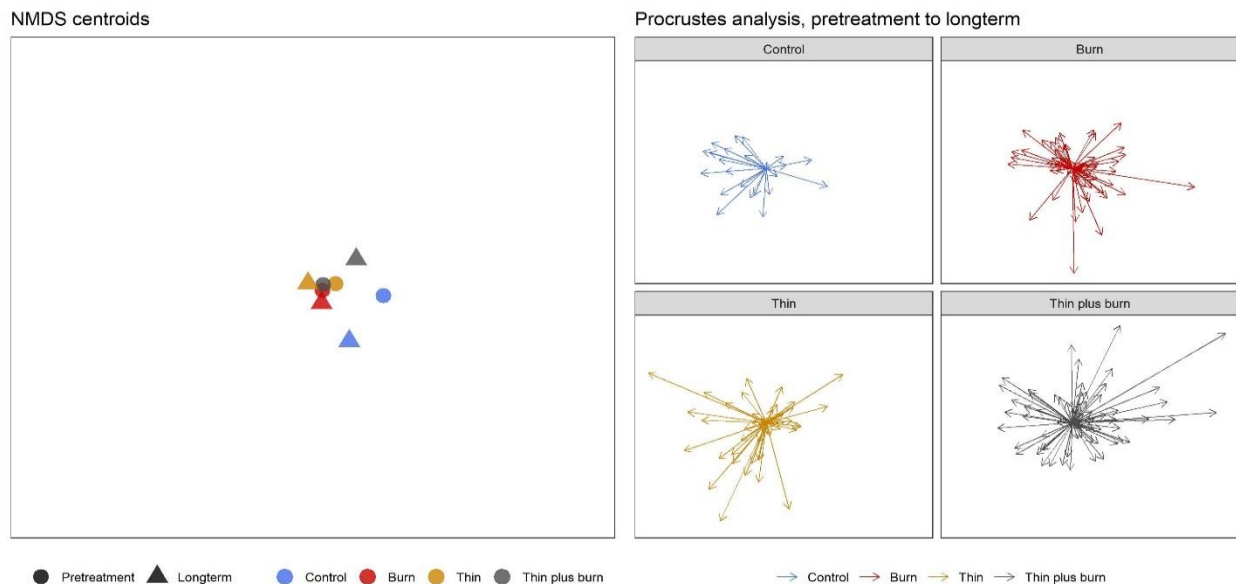

Figure 4: Change in treatment centroids (left) and individual plot scores (right) from pretreatment to longterm.

manner, with greater magnitude of change than treatment centroid movement alone may suggest. The Procrustes analysis also suggested that the movement of the thin plus burn centroid is driven by large movements in a few plots, and not consistent direction of change.

Question 2: *Do plots within a replicate unit and within spatially proximate replicate units will group together in multivariate space in the pretreatment sampling period, and do different replicate units within a treatment category group together after treatment?*

Several clustering methods suggested some pretreatment grouping of replicate units into two groups, one corresponding to the westmost four units, and another corresponding to the eastmost units (figures 5-10). There was crossover between these groups, and the amount of crossover varied by clustering method. The longterm cluster analyses suggest that treatment was associated with a slight increase in intermixing between the groups. Hierarchical clustering with simple, average, and centroid linkage produced results dominated by one group, so I did not present those results in this paper. Dividing the replicate units *a posteriori* into two groups ('west' and 'east') and running the cluster analyses to divide plots into two groups did not reveal strong discrimination between the two clusters of replicate units, with the exception of the *k*-means method (figure 9). Qualitatively I consider any trends seen in cluster analysis to be weak. If I were to present these cluster analyses in a published manuscript I would first research further statistical tests on confusion matrices/classification, and further investigate the characteristics associated with each respective cluster analysis group. The variability in clustering from method to method, and the difficulty I've found in interpreting the results, however, has caused me to question the value of conducting cluster analyses.
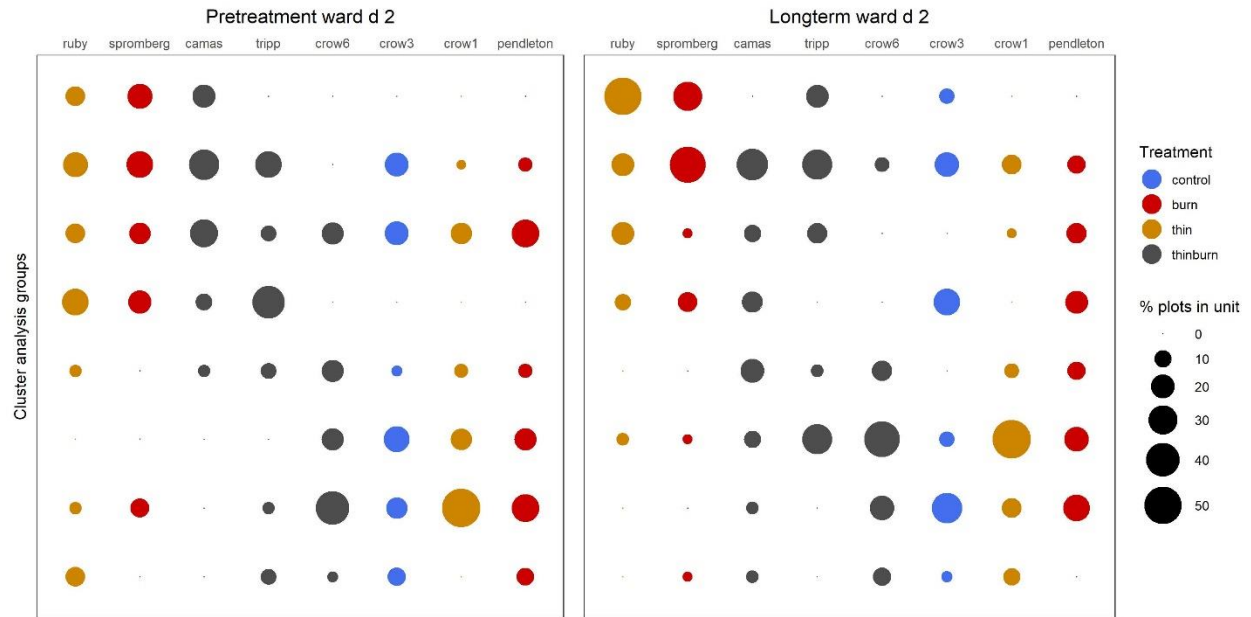
Figure 5: Hierarchical clustering analysis with Ward's method of group linkage. Replicate units on the x axis are arranged by latitudinal position.
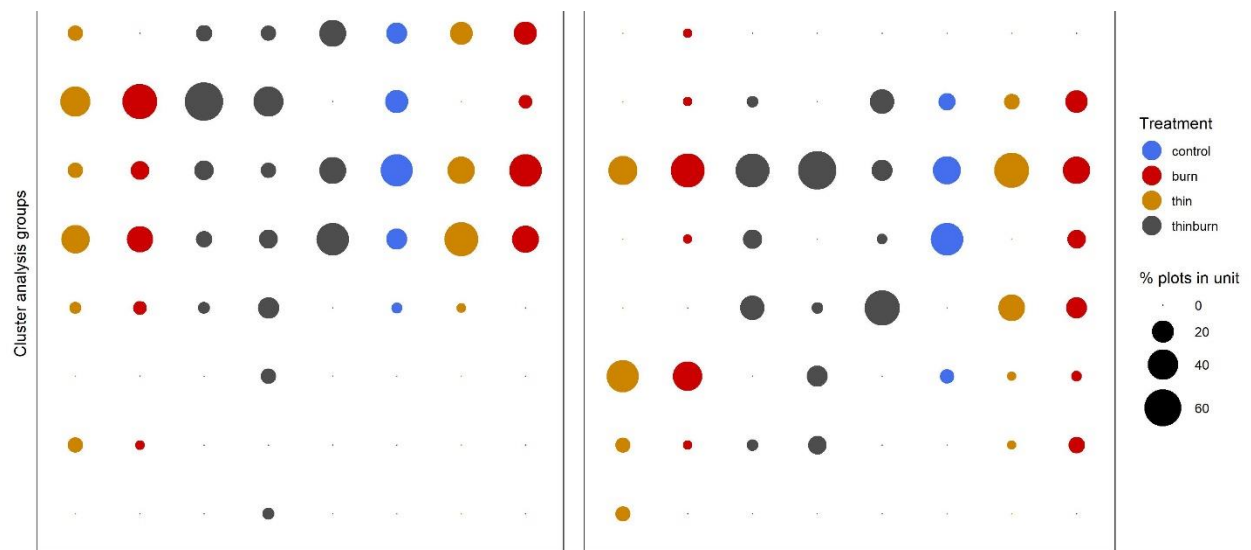

Figure 6: Hierarchical clustering analysis with Ward's method of group linkage. Replicate units on the x axis are arranged by latitudinal position
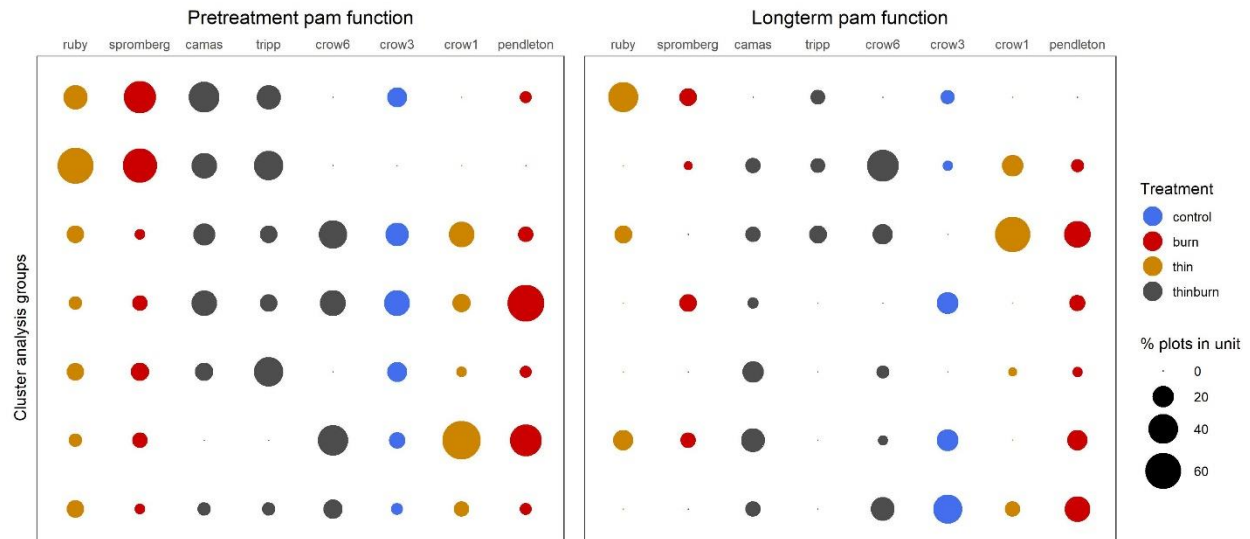
Figure 7: k-means clustering with the cluster::pam() function in R. Replicate units on the x axis are arranged by latitudinal position, order of cluster analysis groups on the y axis is arbitrary.
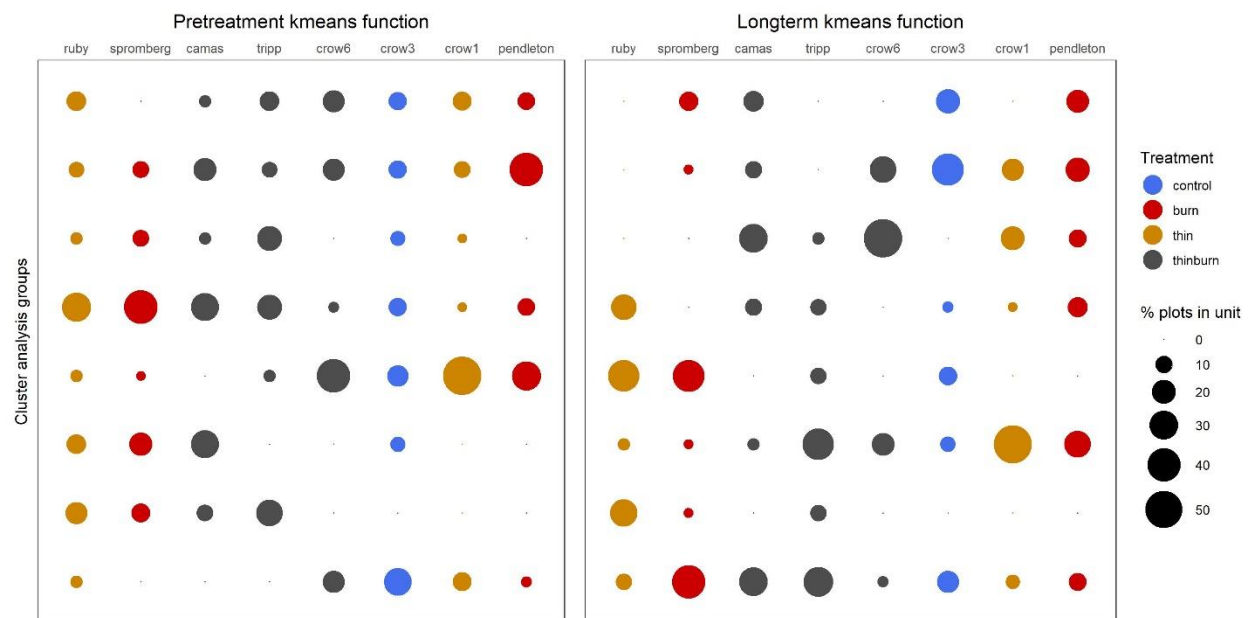

Figure 8: k-means clustering with the stats::kmeans() function in R. Replicate units on the x axis are arranged by latitudinal position, order of cluster analysis groups on the y axis is arbitrary.
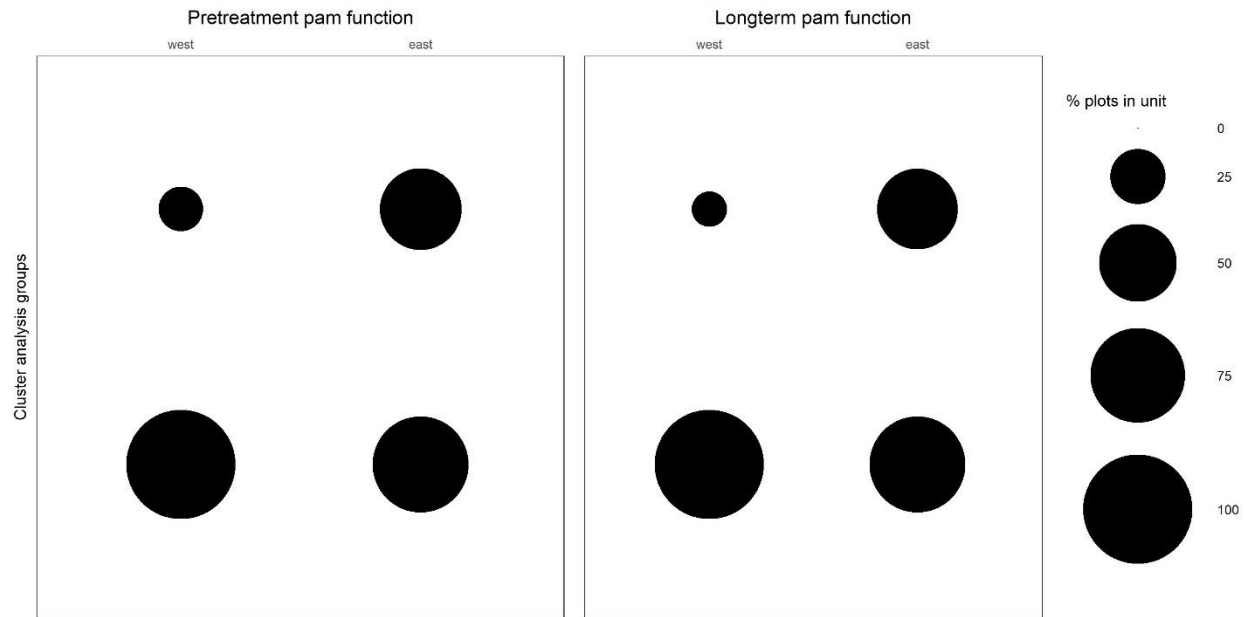
Figure 9: k-means clustering with pam() function, with two groups of replicate units (four westmost and four eastmost) and two cluster analysis groups.
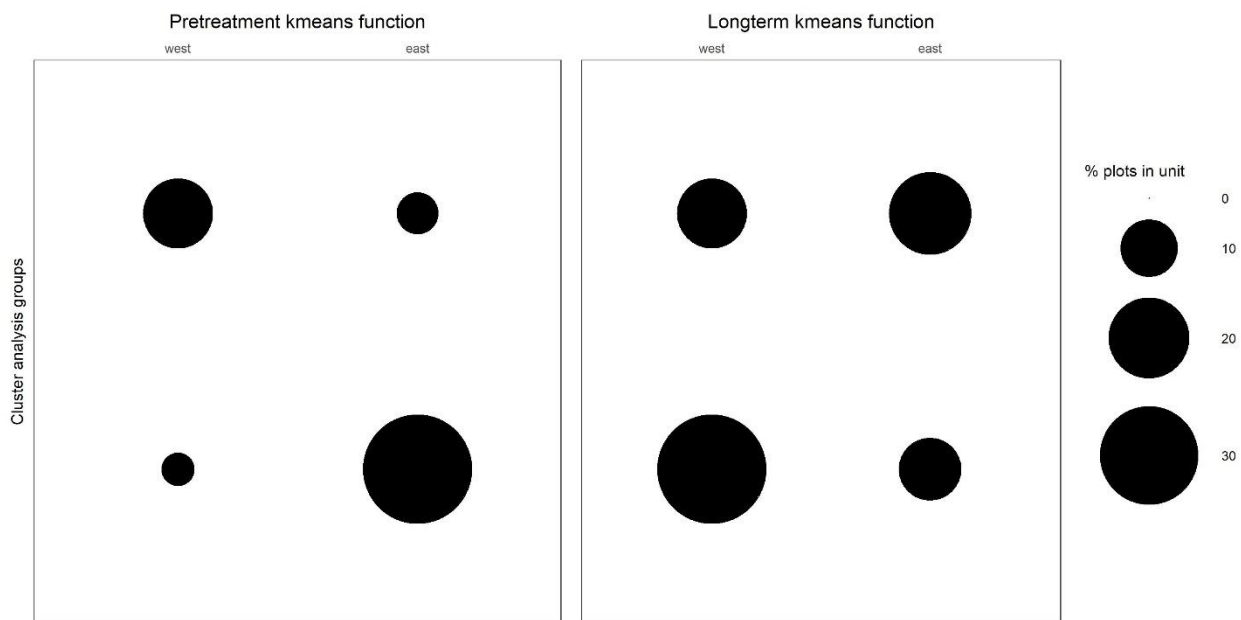

Figure 10: k-means clustering with pam() function, with two groups of replicate units (four westmost and four eastmost) and two cluster analysis groups.

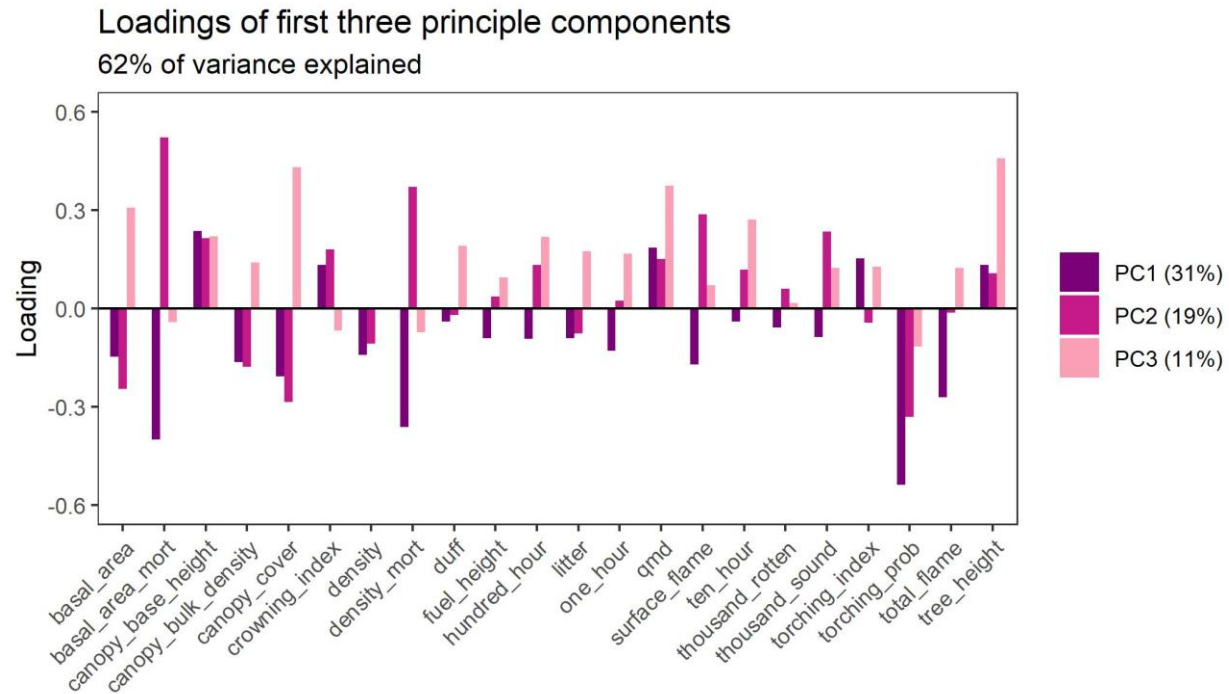*Figure 11: Loadings of first three prinicipal components from the PCA with all response variables.*

Table 1: Response variables with a greater than 0.3 loading for one of the first three principle components of the full PCA.

Sign	PC1 (31%)	PC 2 (19%)	PC3 (11%)
Positive (> 0.3)		Basal area mortality	Canopy cover
		Density mortality	Tree height
		Surface flame	Quadratic mean diam.
		Thousand-hour fuel	Basal area
			Ten-hour fuel
Negative (< -0.3)	Torching probability	Canopy cover,	
	Basal area mortality	Torching probability	
	Density mortality		

Question 3: Could the number of variables needed in analysis potentially be reduced by data reduction methods?

With all response variables run together, principal component one explained 31% of the variance, principal component two explained 19%, and principal component three explained 11% (figure 11). The first two principal components were primarily related to tree mortality and fire behavior, while the third principal component corresponded to more closed canopy positions and later successional status (table 1). The field variables PCA explained less variance, with the first three principal components explaining 56% (figure 12). The modelling variables PCA explained more variance, with 88% explained in the first three principal components and 53% explained by the first principal component (figure 13). The first principal component in the field data PCA was positively associated with stand structure and woody surface fuel, and the first two principal components of the modelling variable PCA were positively associated with tree mortality.

Discussion

NDMS results suggested that assumptions about pretreatment experimental balance may be reasonable, and substantial overlap in ordination space among treatment categories may strengthen my confidence in my univariate hypothesis tests. However, overlap in ordination space may not translate to overlap for all response variables. Additionally, the smaller range of variation for the control treatment category, represented only by one replicate unit after the 2012 Poison Fire, should be considered while interpreting results from all analyses at the study site.
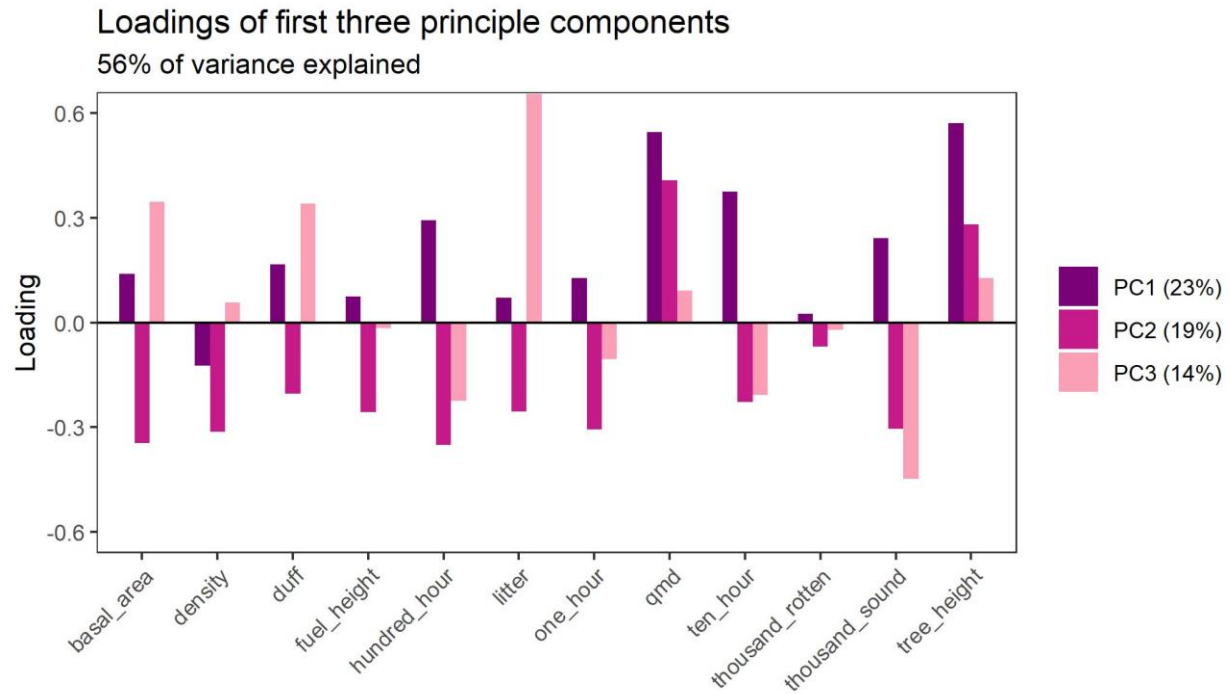
Figure 12: Loadings of first three principal components from the PCA with field variables only.
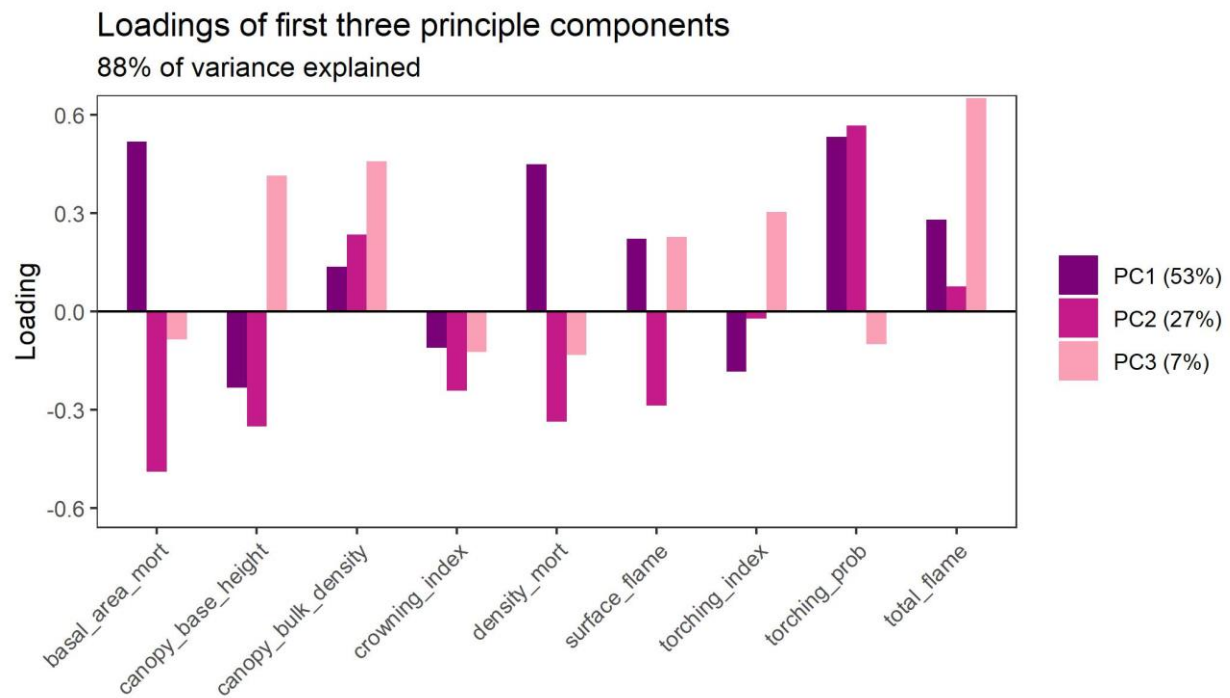

Figure 13: Loadings of first three prinicipal components from the PCA with modelled response variables only.

Movement of treatment category centroids in NMDS space suggest some minor overall effects of treatment. The movement of the thin plus burn centroid towards more open canopy conditions and movement of control treatment towards more closed canopy positions is consistent with expected responses to treatment (Agee and Skinner 2005). The movement of the control centroid provides valuable insight for the burn and the thin treatments, for which the centroids moved little. It is plausible that the true effect of burn and thin treatments may be to delay development towards more closed canopy conditions with more fuels, so that responses appearing not to indicate a longterm effect may still be beneficial compared to untreated stands (Jain et al. 2012). This interpretation should be taken with caution, however, due to having one control unit.

The Procrustes analysis of the two sample periods suggest a wide range of variation in direction and magnitude of plot level responses to treatment, suggesting that factors other than treatment category should be considered by scientists and managers working to understand long term treatment effects. Fuel treatment experiments typically focus on treatment as a categorical variables (e.g. Stephens et al. 2012, Crotteau et al. 2018, Hood et al. 2020), which may weaken statistical power when plot level responses to treatment vary. Treatment intensity often varies widely within a treated stand, both because of variable prescribed fire intensity and intentionally 'clumpy' thinning patterns (Jain et al. 2012). Treatments at my study site were of variable intensity (Agee and Lolley 2006), which may have contributed to the range of NMDS responses to treatment. Other likely influences of longterm plot level response to treatment include topographic position and pretreatment condition (Jain et al. 2012), which I will attempt to account for in my hypothesis testing analyses.

Cluster analysis results slightly suggested some pretreatment clustering into a western and eastern group of replicate units, and some weakening of this geographic clustering from the pretreatment to the longterm sample period, however, results were inconsistent across clustering methods. If the western and eastern groups of replicate units are truly distinct groups, it could affect and/or confound interpretation of statistical tests. The single control unit is of particular concern, because it likely represents the relatively low elevation eastern units better than the higher elevation western units. Although the degree of pretreatment grouping varied widely by cluster analysis technique, nearly all techniques suggest a greater intermixing of the two geographical clusters after treatment. Replicate units in different geographical clusters given the same treatment do not appear to fall into the same cluster analysis group often. This may suggest again that factors other than treatment type, such as treatment intensity or topographic position, affect plot-level responses.

PCAs suggested that field variables were relatively weakly related to one another, and that the most variation in response variables could be explained by modelled tree mortality variables. I believe that PCA is of limited utility for future analyses in this study, based on (what I'm thinking is) a low amount of variance explained by the first principal components, and on difficulties with normality assumptions. Modelled fire severity, however, could be represented by principle components 1 and 2 of the full PCA. This is especially true of tree mortality (both by basal area and density), which was strongly related to the first two principal components of the full PCA and the modelled variables PCA. Modelled tree mortality could be thought of as capturing much of the variation present in the field data, as it incorporates the field data via stand structural data and modelled surface flame length. Many field variables showed a similar sign of response to mortality patterns in principal component 1 and principal component 2 of the full

PCA, but did not have as strong a correlation as mortality. The field variables PCA showed the weakest ability to explain variance with the first principal components. This is not surprising, given the high fine-scale variance of most fuel types, and the inability of most studies to show a strong relationship between stand structure and surface fuel loads (Keane et al. 2001, 2012). Additionally, many of these variables were measured at different scales and/or different points along fuel transects, which may complicate inference when attempting to relate variables at a plot level.

Conclusions

The exploratory analyses presented in this paper will be complimentary to hypothesis testing analyses I will also conduct with the Mission Creek dataset. I found NMDS to be particularly useful here, and will likely further explore the NMDS analyses I've conducted here, for inclusion into the final manuscript. Focus on within-treatment variation is becoming one of the major themes in my manuscript, and the NMDS Procrustes analysis provides clear justification for this focus. The results of the cluster analyses were interesting, but I found them a bit inconclusive. I will keep them in mind, however, as I use mixed effects models with replicate unit set as random effect. It's possible that the random intercept scores of the western four units will be in one direction, and the random intercept scores of the eastern four units will be in another direction. Or it's possible that other explanatory variables used in the models, such as heat load index, will partially account for differences between geographic clusters. In any case, I'll have a more concrete idea of possible confounding effects after running the cluster analyses. I am unlikely to use PCA results presented here for further hypothesis testing, partially because of concerns with PCA in this context and difficulty with variable transformation, and

partially because of my preference for dealing with individual variables in hypothesis testing. However, PCA has shed light on possible relationships between response variables, which will be interesting to compare to univariate hypothesis testing results of different response variables.

In sum, these multivariate analyses have helped to clarify or suggest patterns in a dataset that's complicated in several dimensions, including some experimental imbalances, geographic differences in replicate units, and large number of partially related response variables. These results will be complimentary to hypothesis testing analyses moving forward, and the NMDS will likely prove an integral piece of my Mission Creek dissertation chapter and manuscript.

Appendix One: Metadata

Mission Creek Fuel Data Description and Metadata

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The following report describes fuel data from the Mission Creek site of the Fire and Fire Surrogates Study (FFS). The data described are contained in the 'mission_master_widest.csv' file. Additional sample protocols are listed in the 'protocol_mission_creek_2020.doc' file.

The Mission Creek site was one of original 13 sites of the FFS, a nationwide coordinated distributed experiment designed to study the effects of the following forestry treatments: control, thin, burn, and thin plus burn (McIver and Weatherspoon 2010). The four treatments were implemented in 2001-2006 at the Mission Creek site, over three replicate units of roughly ten hectares each for each treatment (Agee and Lehmkuhl 2009). In 2012, a low severity wildfire burned through four of the replicate units: two control, one thin, and one burn (Rossman et al. 2020). See protocol document for more details.

The fuel data used in analysis includes two sample periods, called here 'pretreatment' and 'longterm.' Pretreatment data were collected in 2000, and collection was led by James Agee of the University of Washington (Agee and Lolley 2006, Agee and Lehmkuhl 2009). Longterm data were collected in 2019 and 2020, and collection was led by Don Radcliffe and Brian Harvey of the University of Washington. Immediate post treatment response data were also collected, and results are documented in Agee and Lolley (2006), but at the time of writing this report these data have not been relocated in raw form.

The goal of the current analyses is to analyze whether treatments affected fuel loading in the long term (greater than one decade following treatment, in our dataset 13-18 years following final treatment), and whether pretreatment differences in replicate units affected the long-term response. The fuel components that will be analyzed are detailed in the text below. Surface fuel data were collected and summarized using Brown's transects (Brown 1971), with two transects per plot. More details of the Mission Creek Brown's transects are outlined in Agee and Lolley (2006) and the attached protocol document. Tree attributes were collected and summarized from fixed area radius plots, the details of which are described in the attached protocol document.

All longterm data were double-checked after entry, and each column was graphed to check for outliers. Additional data files/scripts are available upon request. All data, metadata, and

analyses are saved and version controlled on Don's github page (don-radcliffe). The repository is currently private, but will be made public once a publication is produced from the longterm Mission Creek data.

The following table lists metadata for response variables used in the SEFS 502 final report. Note that for fire modelling variables, I've presented the 'moderate' fire weather and fuel conditions, which were determined from 80th percentile conditions using procedures described briefly below and in more detail in the report. In the 'mission_master_wide' .csv, these variables are also available using 'mild', 60th percentile, and 'severe', 97th percentile, conditions. Additionally, basal area and density mortality variables are available with a 'null' model, in which a four foot surface flame-length was applied to every plot in the dataset.

Response Variable Metadata

variable	units	explanation
plot	categorical	Sample plot the raw data were collected from, combined into the unitname_plotnumber format because plot numbers duplicated across different replicate units.
period	categorical	Sample period. 'pretreatment' was collected 1-6 years before treatment, in the year 2000. 'longterm' was collected 14-19 years after treatment, in 2019 & 2020.
basal_area	meters_squared_per_hectare	Basal area calculated from raw plot data (tree diameters). Potential range 0-infinity.
density	trees_per_hecatare	Tree density calculated from raw plot data. Potential range 0-infinity.
qmd	centimeters	Quadratic mean diameter of trees on a plot. Potential range 0-infinity.
one_hour	megagrams_per_hectare	One hour fuels; surface woody fuels between 0 and 0.64 centimeters in diameter. Potential range 0-infinity.
ten_hour	megagrams_per_hectare	Ten hour fuels, surface woody fuels between 0.64 and 2.5 centimeters in diameter. Potential range 0-infinity.
hundred_hour	megagrams_per_hectare	Hundred hour fuels, surface woody fuels between 2.5 and 7.6 centimeters in diameter. Potential range 0-infinity.
thousand_sound	megagrams_per_hectare	Thousand hour fuels in decay classes 1-3, surface woody fuels greater than 7.6 centimeters in diameter. Potential_range 0-infinity.
thousand_rotten	megagrams_per_hectare	Thousand hour fuels in decay classes 4-5, surface woody fuels greater than 7.6 centimeters in diameter. Potential range 0-infinity.
fuel_height	centimeters	Maximum height of dead woody fuel, averaged over multiple sample locations in plot. Potential range 0-200.
litter	megagrams_per_hectare	Biomass of forest litter layer, measured and summarized using the protocol of Brown, J.K. 1974. Potential range 0-infinity.
duff	megagrams_per_hectare	Biomass of duff layer (partially decomposed organic material of which parent source is unrecognizable). Potential range 0-infinity.
shrub	megagrams_per_hectare	Biomass of shrub layer, sampled and summarized using the protocol of (Burgan and Rothermel 1984). Potential range 0-infinity.

herb	megagrams_per_hectare	Biomass of herb layer, sampled and summarized using the protocol of (Burgan and Rothermel 1984). Potential range 0-infinity.
canopy_base_height	meters	Canopy base height, estimated from stand structural data using FVS-FFE program version 3431 (Reinhardt and Crookston 2003). Potential range 0-infinity.
canopy_bulk_density	megagrams_per_hectare	Canopy bulk density, estimated from stand structural data using FVS-FFE program version 3431. Potential range 0-infinity.
surface_flame	meters	Surface flame height, estimated from fuel data using FVS-FFE program version 3431, with 80% percentile weather and fuel moisture parameters for June 15 – September 15 of 2002-2017, determined from Fire Family Plus (Bradshaw and McCormick 2000). Potential range 0-infinity.
total_flame	meters	Total flame height including surface and crown fire, estimated from fuel data using FVS-FFE program version 3431, with 80% percentile weather and fuel moisture parameters for June 15 – September 15 of 2002-2017, determined from Fire Family Plus. Potential range 0-infinity.
torching_index	kilometers_per_hour	20 foot windspeed that is expected to ignite the crown layer, estimated from fuel and stand structure data using FVS-FFE program version 3431, with 80% percentile weather and fuel moisture parameters for June 15 – September 15 of 2002-2017, determined from Fire Family Plus. Potential range 0-infinity.
torching_probability	percent	Probability of 'finding a small area' that will torch under the fire weather and fuel moisture conditions given. , estimated from fuel and stand structure data using FVS-FFE program version 3431, with 80% percentile weather and fuel moisture parameters for June 15 – September 15 of 2002-2017, determined from Fire Family Plus. Potential range 0-100.
crowning_index	kilometers_per_hour	20 foot windspeed that is expected to maintain an active crown fire, estimated from fuel and stand structure data using FVS-FFE program version 3431, with 80% percentile weather and fuel moisture parameters for June 15 – September 15 of 2002-2017, determined from Fire Family Plus. Potential range 0-infinity.
density_mortality	Percent	Percentage of tree stems that would die in a simulated wildfire, estimated using FOFEM version 6.7 (Reinhardt et al. 1997) with stand structural data and FVS-FFE 3431 modelled surface flame. Potential range 0-100.
basal_area_mortality	Percent	Percentage of basal area that would die in a simulated wildfire, estimated using FOFEM version 6.7 (Reinhardt et al. 1997) with stand structural data and FVS-FFE 3431 modelled surface flame. Potential range 0-100.

The following predictor variables were not used in 502 analyses, but I've included metadata on them here, because they are contained within the mission_master_widest.csv data.

Predictor variable metadata

column	units	explanation
plot	categorical	Sample plot the raw data were collected from, combined into the unitname_plotnumber format because plot numbers duplicated across different replicate units.
elevation	meters	Elevation derived from a 10m resolution Digital Elevation Model. Potential range 0-infinity.
slope_percent	percent	Slope angle derived from a 10m resolution Digital Elevation Model. Potential range 0-infinity.
transformed_aspect	cosine	Aspect transformed using the equation $(\cos(45° - aspect) + 1)$. Equation from (Beers et al. 1966). Potential range 0-2.
treatment	experimental_treatment	One of four experimental treatments: control, burn, thin, or thin plus burn. Also 'wildfire' for control units hit by a subsequent low severity wildfire. See protocol for more detail.
unit	replicate_unit	One of 8 individual replicate units, each approximately 10 hectares in size, each with an experimental treatment applied. See protocol for more detail.
topographic_wetness index	index	Topographic wetness index calculated from a 10 meter digital elevation model using the RSAGA package in R. Potential range 0-10.
heat load index	index	Heat load index calculated from 10-meter digital elevation model using the spatialEco package in R. Potential range 0-1.
rdnbr	index	Relativized normalized burn index, calculated without offsets using growing season image composites analysis in Google Earth Engine (Gorelick et al. 2017) with code from (Parks et al. 2018), updated in 2021 to resolve a mistake found in the original code. Potential range -infinity-infinity.
thinning_intensity	index	Average of relativized change in basal area and relativized change in live canopy cover from pretreatment to longterm sample periods, with relativization by maximum. Potential range 0-1.

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