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SEFS 502 Analytical Methods Assignment

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**Published Methods**

My primary analysis goal related to this class is to run an ordination analysis, likely an NMDS, on my fuel and modelled fire behavior variables. See the Analytical Methods section for more details on my study and proposed analyses. I can’t remember reading any fuel-focused studies that have used ordination to see how fuel treatment or time affects fuel loads, and I could not find any such studies in a quick Google Scholar search. However, I know that ordinations are more commonly used for other response variables such as soil and understory communities. With a very quick search I found two soil studies that used NMDS to help test the effects of fuel treatments on soil variables on Fire and Fire Surrogates network related projects (Boerner et al. 2009, Miesel et al. 2011; both with Ralph Boerner as an author). My data is from one of the Fire and Fire Surrogates sites, so I share the same overarching experimental study design. The Fire and Fire Surrogates network is a nationwide coordinated distributed experiment on thinning, burning, and prescribed conducted at twelve sites across the US, started in the early 2000s. I decided to evaluate soil studies for this assignment because I think they share some similarities with fuel studies: both fuel and soil studies are likely to have many positive continuous variables with no upper bound, unlikely to have many zeros/rare variables, and unlikely to have all variables share the same units or rough magnitude of variation.

Miesel et al. (2011) used an NMDS to help assess the effects of treatment and time on soil variables at the southern Cascades Fire and Fire Surrogates site in northern California. They did not state hypotheses, and their study questions were fairly general; the implied hypothesis was that fuel treatments would affect soil properties and that the effects would vary over time. They used 15 physical, soil, and chemical parameters in the ordination. To account for the different units of different types of variables, they standardized all variables by mean and standard deviation. They used Euclidean distance. Their unit of replication was experimental replicate unit (three replicates of about ten hectares each for four treatments). Each unit consisted of several (averaged?) subsamples. Each unit was measured twice, once one year after treatment and once three years after treatment. On the NMDS plot, they used symbols to represent treatment type and colors to represent sample period. The major conclusions drawn from this analysis were that thin and thin plus burn had the greatest influence on soils, and had fairly similar influences to one another. Additionally, the observed effects of thin and thin plus burn treatments were larger in year one than year three, judging by those points’ positions along axis 2 of the NDMS (Miesel et al. 2011).

Boerner et al. (2009) used an NMDS of metanalytical effect sizes of treatment on 12 soil variables, to visualize the effects of treatment on soil properties across the 12 site Fire and Fire Surrogate network. They listed four hypotheses related to treatment effects on soil variables, which I will not list here because the hypotheses were more directly addressed using traditional meta-analysis, and were multifaceted and related to specific soil variables. The authors used study site as the unit of replication, and also plotted a point for the across network mean of each treatment type. They ran two separate NMDS: one for one-year post treatment, one for three years post-treatment. The broad conclusions from the NMDS portion of the paper were that regional differences overshadowed treatment differences, particularly one year post treatment, but that some treatment types had broadly consistent effects within a region (particularly thin and thin plus burn treatments in the western US). Additionally, network means suggested that thin plus burn had a greater effect on several soil properties than either of the other treatments.

**Data Matrices**

I’ve focused most of my attention this quarter on producing my data matrix with all response and predictor variables represented on a plot and sample period level, and was able to finish pre-processing data recently. I’ve attached this ‘master’ table in three formats: long (tidy), wide, and ‘widest’. Wide has my two sample periods represented by one column, while widest has each response variable represented in two columns, one for each period. Graphing variable distributions is easiest with the tidied data, ordination will likely require the wide format, and my generalized linear mixed models will require the widest format because I’m using pretreatment value as a predictor variable. All data processing after initial data entry checking was performed in R, so it will be easy to make any necessary adjustments or corrections and reproduce my tables. This is with the exception for use of two fire models that are run using point and click interfaces, FVS-FFE and FOFEM, for which I preformatted and postprocessed all data using R. All data and scripts are backed-up and version-controlled using GitHub.

My available plot-level predictor variables are elevation, slope, transformed aspect, coordinates, topographic wetness index, topographic heat load index, thinning intensity index (will explain that further in an upcoming email), and burn severity measured by RdNBR. My available plot-level response variables include basal area, tree density, tree quadratic mean diameter, tree height, average height to canopy base (field), one hour fuels, ten hour fuels, hundred hour fuels, thousand hour sound fuels, thousand hour rotten fuels, litter, duff, fuel height, canopy cover, canopy bulk density (FVS), canopy base height (FVS), surface flame height (FVS), total flame height (FVS), torching index (FVS), crowning index (FVS), torching probability (FVS), potent smoke (FVS), basal area mortality (FOFEM), density mortality (FOFEM), and density mortality of all trees greater than four inches (FEM). FVS-FFE fire behavior metrics are all available in three severity classes: mild (60th percentile conditions), moderate (80th percentile conditions), and severe (97th percentile conditions, and calculated with 97th daily max wind and temperature instead of mean). FOFEM tree mortality metrics are available in four severity classes, using flame lengths from the mild, moderate, and severe FVS-FFE model runs, plus a ‘null’ FOFEM default flame length of four feet applied across each plot, run to isolate tree resistance from fuel load.

**Study Questions**

1. How does treatment type, pretreatment condition, treatment intensity, and site productivity affect a) fuel loads, b) expected fire behavior and c) expected forest resistance to fire, 13-18 years after treatment, at the plot-scale?

* Analyses: Generalized linear mixed models, nonmetric-multidimensional scaling

1. How does treatment affect plot-level variation within and between sample units, 13-18 years after fire?

* Analyses: Nonmetric multidimensional scaling, cluster analyses

**Hypotheses**

1. I expect that treatment type will have less effect on response variables than treatment intensity, site productivity, and pretreatment condition. This is based on other fuel treatment longevity studies failing to find significant effects of categorical level treatment on most fuel variables while acknowledging variability within replicate units (Stephens et al. 2012a, Hood et al. 2020, Morici and Bailey 2021), and on high variability observed in earlier studies at my site (Agee and Lolley 2006). I expect the thin plus burn treatment will have a greater negative effect on fuel loads and fire behavior than either treatment alone, and a greater positive effect on forest resilience to fire, based mostly on short-term fuel treatment studies (i.e. Schwilk et al. 2009, Stephens et al. 2012b) with some limited results from long-term fuel treatment studies (Hood et al. 2020, Morici and Bailey 2021). I expect that treatments will have little impact on the expected results of extreme fire (Reinhardt et al. 2008), based on retrospective remote sensing analyses (Prichard et al. 2020).
2. I expect there will be as much or more variation in multivariate space within units as among units. This is based on observed variation in my study site (Agee and Lolley 2006), my field experience with the study site, and on the moisture-limited and therefore variable nature of dry forest types. I expect that my relatively low elevation east-most units (Pendleton, Crow1, Crow3 and Crow6) will form a distinct group, and that the west-most higher elevation units (Camas, Ruby, Spromberg) may form another distinct group. I expect that treatment will reduce the variation among units with the same treatment, although not to a qualitatively great degree in the longterm period.

**Analytical methods**

*Question 1*

I will address Question 1 by using generalized linear mixed models (glmms) and

nonmetric-multidimensional scaling (nmds).

The glmms will allow for plot level analyses while accounting for potential within-unit psuedoreplication by treating unit as a random effect. Models will likely use a gamma distribution with a log link, which allows for modelling positive continuous variables and can account for right skewed distributions, which many of my variables display. Error distributions will be checked to ensure model assumptions are met. I plan to use semivariograms to check for spatial autocorrelation, but don’t expect spatial autocorrelation to be a major concern given high spatial variability in fuel variables and in dry forests generally. Fixed effects will likely be pretreatment value for the response variable, topographic heat load index, relative differenced normalized burn ration (RdNBR), thinning intensity, thin (binary), burn (binary), and thin ~ burn interaction. Response variables are listed above in the ‘Data Matrix’ section, and for fire modelling products I will use moderate fire weather conditions as response variables for this analysis. Models for each response variable will retain the full set of terms for analysis, to allow direct comparison of significance and effect sizes among models (Burnham and Anderson 2002). Inference will be made by assessing 95% confidence intervals and the effect size of each model term.

The nmds analysis will be used to qualitatively support the glmm analysis. In the nmds plot, fuel loading and expected fire behavior and effects will be represented as points colored by unit and shaped by treatment. Two such plots will be produced, one for pretreatment values, one for long-term

values. The plots will show both direction and magnitude of change in multivariate space, which will illuminate the effect of treatment given the symbology will separate units and treatments. I would also like to overlay the predictor variables on the visual plot, even though the nmds is an unconstrained analysis that doesn’t formally put estimates on predictor variables, because I think it will shed light on the contributions of other variables. Additionally, the information reduction will be useful in showing which response variables may be related to one another via both axis scores and the visual plots, which will shed light on how much variation there is among different fuel types at a within-plot scale. Before analysis, I will standardize the variables to account for the different units and magnitudes of variation of the different variables in my dataset. I will likely use a Euclidean distance matrix like the soil papers I discussed above, because are continuous and symmetric (shared absences are likely to be meaningful). I will likely experiment with the number of axes needed, as I don’t have a great a priori expectation for that. I plan to use a non-metric ordination because the complexity of my dataset makes it seem unlikely that I can meet assumptions of parametric tests like PCA. I do not plan to run any formal significance tests using the nmds results, because I’m considering the nmds to be qualitative support for my glmms.

*Question 2*

Assessing variability in the dataset was the original inspiration for the nmds analysis, because my study site is known to be highly variable, which could cause issues in interpretations of results. I also believe that a cluster analysis could be useful here to gauge whether the different replicate units are distinct from one another in multivariate space.

The nmds visuals will be used to assess whether similar treatments cause units to become more similar to one another in the longterm, whether plots within a treatment become more similar to one another in the longterm, and how the starting point of a unit affects its trajectory after treatment. These questions are interesting from an ecological standpoint, in that they allow us to explore some nuance in how the same treatment may have different results depending on starting condition. They are also interesting from a study design and inference perspective, because they may help us understand where variation among experimental replicates could lead to spurious conclusions from summary statistics and glmms.

I’m also interested in performing cluster analyses to determine whether plots are strongly grouped by their respective replicate units, both before and after treatment. The notes suggest that inference may be improved by conducting multiple cluster analyses, so I plan to conduct a (non-hierarchical) k-means cluster analysis, an agglomerative hierarchical cluster analysis (likely a hierarchical polythetic agglomerative cluster analysis with simple linkages), and a divisive hierarchical cluster analysis (perhaps a hierarchical polythetic agglomerative cluster analysis with simple linkages). I plan to prune the dendrogram at 8 groups, which is the number of replicate units at my site, and see if the units group differently before and after treatment. If the units are strongly grouped before treatment, this may indicate issues with the experimental assumption of pretreatment homogeneity. We already know there are issues with that assumption, and are attempting to account for them with the glmm analyses, but the grouping may help us better understand the issues. Additionally, if there is a major difference in grouping between the pretreatment and longterm sample period, this could indicate treatment effects. My confidence in the grouping will depend on the consistency between the different methods. This analysis can be complementary to the NMDS, and we can overlay the grouping onto the NMDS to further assess variation between and among groups, if the overlay doesn’t get too confusing with everything else going on in the NMDS!

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