THESIS

# IMPROVING ASSESSMENTS OF FUEL TREATMENT EFFECTS ON SURFACE FUELS IN PONDEROSA PINE FORESTS OF THE SOUTHERN ROCKY MOUNTAINS


Submitted by

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# ABSTRACT

## IMPROVING ASSESSMENTS OF FUEL TREATMENT EFFECTS ON SURFACE FUELS IN PONDEROSA PINE FORESTS OF THE SOUTHERN ROCKY MOUNTAINS

Fuel hazard reduction treatments have been widely employed in dry forests of the western United States in recent decades in response to the increasing extent and severity of wildfires. In order to design and accurately assess the effects of these fuel hazard reduction treatments, accurate fuel inventories are required. However, obtaining accurate assessments of fuelbeds is complicated by a lack of knowledge about the effects of treatments on surface fuels and their spatial distribution. This thesis focuses on enhancing knowledge of treatment effects on surface fuels in ponderosa pine sites across Colorado and New Mexico, USA.

The primary emphasis is on Chapter 1, which focuses on the spatial distribution of surface fuels and how it is changed by fuel hazard reduction treatments. I found that total surface fuel loads were reduced by ~10% in thinned sites and ~50% in thinned and burned sites. Semivariance following thin and burn treatments was similar to untreated sites and lower than thin-only sites for all fuel components except 1,000-hr fuels, with fuel component semivariance being highly predictable ($R^2$=0.99) from fuel component mean fuel loading. The scale of spatial independence for all fuel components and sites ranged from <1-50 m with the shortest spatial scales occurring for the finest fuel components (i.e. duff, litter, etc.). Mean fuel particle diameter strongly predicted ($R^2$=0.88) the distance needed to achieve sample independence. Incorporating such knowledge of spatial variability into fuel sampling protocols will enhance assessment of wildlife habitat and fire behavior and effects modeling over singular stand-level means.

Chapter 2 focuses on the physical characteristics of fuel particles present before and after fuel hazard reduction treatments. I report mean squared diameter ($d^2$) values for downed dead woody surface fuels that can be used to improve fuel loading assessments using the widely applied planar intersect sampling protocol. The planar intersect method requires an approximation of the mean squared diameter ($d^2$) of 1, 10, and 100-hr timelag size classes to create loading estimates for downed dead woody surface fuels. I analyzed woody surface fuels collected throughout the southern Rocky Mountains to create local $d^2$ estimates for untreated, mechanically treated, and mechanically treated and broadcast burned sites. Resulting estimates were up to 38% higher in the 1- and 10-hr classes and 28% lower in the 100-hr classes when compared to previously published values from other regions. The new burned partially harvested values for 1- and 100- hour classes were also roughly 20% lower than in the other stand conditions.

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# CHAPTER 1: FUEL TREATMENT EFFECTS ON SPATIAL VARIABILITY OF SURFACE FUELS IN PONDEROSA PINE FORESTS OF THE SOUTHERN ROCKY MOUNTAINS

## 1.1 Introduction

Wildland fuels are remarkably complex across space and time, which makes them inherently difficult to describe accurately (Keane 2013). The most common variable used to describe any given fuel component is fuel loading (kg $m^{-2}$) because this value is required for many operational fire behavior and effects models and is a key variable in fuel hazard assessment. This is particularly important in the context of fuel reduction treatments because fuel loading both helps to determine the need for fuel treatments and in assessing the treatment effectiveness. Numerous studies have quantified fuel loadings across a wide range of ecosystems (Brown and Bevins 1986; Wadleigh et al. 1998; Hély et al. 2003; Hille and Ouden 2004; Stephens 2004) and assessed the effect of various disturbances on fuel load including mechanical fuel treatments and prescribed fire (Stephens and Moghaddas 2005; Stephens et al. 2009; Scott 1998; Sackett 1980a), insect outbreaks (Page and Jenkins 2007, Hoffman et al. 2012a), pathogens (Hoffman et al. 2007; Valachovic et al. 2011), wind (Woodall and Nagel 2007), and wildfires (Storm and Fulé 2007). However, there is a lack of information regarding the inherent spatial scale of fuel variability across various ecosystems, or the effects of abiotic and biotic disturbances on how fuels are distributed through space.

While there is a growing understanding of how fuel spatial variability may govern the impact of fire on an ecosystem, there remains a lack of understanding of how fuels vary through space. Studies across the United States and Australia, in ecosystem types including tall grass prairie, pine savanna, and eucalyptus forests, have found that patterns in fire behavior are strongly affected by fine scale (i.e. 0.5-10 m) heterogeneity in surface fuels (Gibson et al. 1990; Hobbs and Atkins 1988; Thaxton and Platt 2006; Hiers et al. 2009). Variability in fuel consumption, maximum surface temperatures reached, soil heating, rate of spread, flame height, and shrub mortality corresponded to fuel distributions at scales of 0.5 to 10 meters depending on the ecosystem. These differences in fire behavior are likely to lead to corresponding spatial variation in fire effects like seed-release, germination, and post-fire vegetation recovery (Hobbs and Atkins 1988; Thaxton and Platt 2006).

One way to characterize the inherent spatial scale of fuel variability is the characteristic length scale (CLS)—the inherent scale at which a process or characteristic occurs over an area (Carlile et al. 1989) and at which the dynamics of the system are most clearly observed (Habeeb et al. 2005). Samples collected at scales smaller than the CLS are likely to be overwhelmed by strong correlations between samples, potentially obscuring the identification of true system dynamics, whereas samples collected at scales much larger than the CLS are likely to average out important dynamics of the system (Keeling et al. 1997; Habeeb et al. 2005). Although the concept of CLS has most often been used in modeling competition in ecological systems, it has recently been applied to investigations of fuel components (Kalabokidis and Omi 1992; Hiers et al. 2009; Keane et al. 2012a). Understanding this spatial scale can inform optimal sampling designs for fully characterizing the spatial distribution of fuel loading on a site, or for most efficiently placing samples for accurate mean loading and variance estimates.

Previous research has suggested that wildland fuel loads are highly variable at a fine resolution (Kalabokidis and Omi 1992, Reich et al. 2004, Hiers et al. 2009, Keane et al. 2012b) and that the CLS is likely to differ between fuel particles of varying sizes (Keane et al. 2012b). For example, Keane et al. (2012b) found CLS of fuel loads for surface fuels less than 7.6 cm in diameter tended to vary at scales ranging from less than 1 m to around 20 m, while 1000-hr fuel loads had CLS that varied from 20 to 160 m across a wide range of western North American ecosystems. Kalabokidis and Omi (1992) found a CLS of 20 to 30 m for total fuel loading in lodgepole pine (*Pinus contorta*) forest types and 60 m for big sagebrush (*Artemisia tridentata*) dominated ecosystems. Although this previous research has provided a framework to begin to understand the CLS associated with surface fuels it is still limited to a small number of locations and it is unknown what effect management actions have on the inherent spatial scales of variability.

The overall goals of this study were to quantify the fuel loading, fuel loading variability, and the CLS of fuel loading by surface fuel component in untreated, mechanically treated, and mechanically treated and burned ponderosa pine forests of the southern Rocky Mountains. Additionally, we assessed the relationship between fuel component size and the CLS and the relationship between surface fuel load variability and total surface fuel load in order to create scaling relationships linking our spatial variability measures to more readily measured fuel characteristics.

## 1.2 Methods

### *1.2.1 Study Sites*

Six sampling locations across the southern Rocky Mountains were selected to represent a wide range of ponderosa pine forests and current fuel treatment prescriptions across the region (Figure 1.1). Sites were chosen in consultation with regional and local USDA Forest Service personnel and were limited to areas that contained treated (either thinned or thinned and broadcast burned) and untreated stands that were (1) within 10 kilometers of each other; (2) of similar overstory composition; (3) relatively flat, with an average slope of less than 5%, although small areas of up to 30% were included; (4) large enough to accommodate a 9 ha plot; and (5) accessible within 2.5 km of a road. Untreated plots accompanied each treated plot and where possible they were installed in areas slated for future fuels reduction treatments to minimize selection bias due to pre-treatment stand differences.

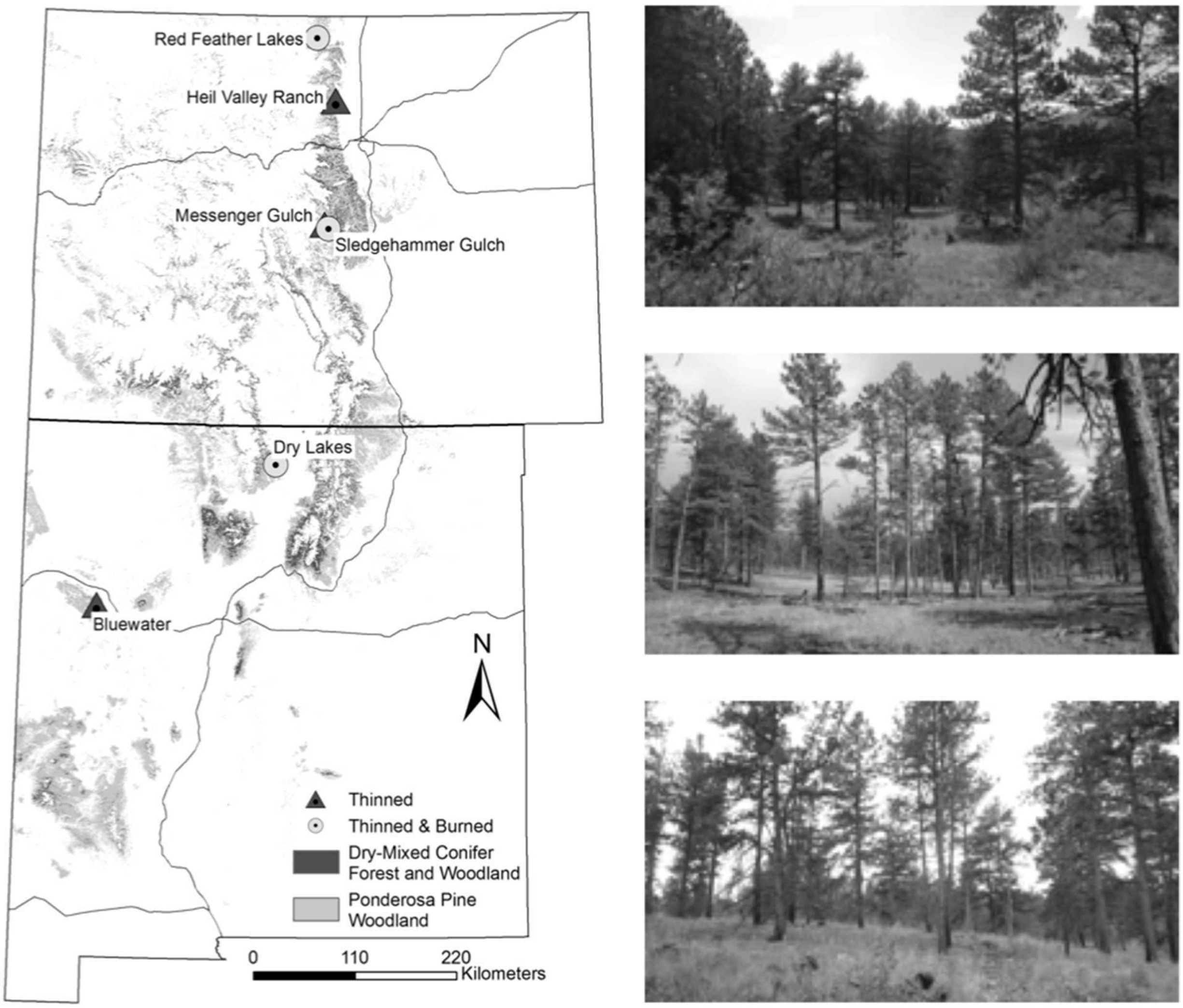


***Figure 1.1****: Location of the six ponderosa pine-dominated study locations across the southern Rocky Mountains used in this study. Each treated stand location was paired with an unmanaged adjacent site.*

Ponderosa pine was the dominant overstory tree species at all sites, ranging from 72 to 100% by basal area (Table 1.1). Elevation ranged from 2000 to 2800 m, covering the elevational distribution of ponderosa pine forests in this region (Peet 1981, Dick-Peddie 1993). Other species found on our sites included quaking aspen (*Populus tremuloides*), Douglas-fir (*Pseudotsuga menziesii*), and blue spruce (*Picea pungens*). Quadratic mean diameter of the overstory ranged from 27.6 to 41.2 cm in untreated sites, 28.8 to 45.5 cm in thinned sites, and 33.5 to 37.2 cm in thinned and burned sites. Tree density ranged from 101 stems per hectare in the thinned site at Bluewater to 1287 stems per hectare in the untreated site at Heil Valley Ranch. Basal area ranged from 6 to 30 $m^2$ $ha^{-1}$.

***Table 1.1*** *General description of study sites. Values in parentheses represent standard deviation at variable radius plot-level. Species composition is given by basal area.*

| Site | Treatment | QMD (cm) | TH (m) | BA ($m^2$ $ha^{-1}$) | Density (stems $ha^{-1}$) | Species Composition |
|---|---|---|---|---|---|---|
| Heil Valley Ranch | Untreated | 27.6 (8.3) | 9.6 (1.8) | 30 (16) | 1287 (1179) | PIPO (100%) |
| | Thinned | 28.8 (8.7) | 9.1 (1.5) | 15 (10) | 383 (294) | PIPO (100%) |
| Bluewater | Untreated | 29.5 (6.5) | 11.5 (2.0) | 19 (8) | 541 (413) | PIPO (100%) |
| | Thinned | 45.5 (14.6) | 16.0 (4.9) | 6 (5) | 101 (220) | PIPO (87%)<br>PIED (8%) |
| Messenger Gulch | Untreated | 41.8 (11.8) | 13.9 (2.6) | 14 (9) | 301 (479) | PIPO (87%)<br>PSME (11%) |
| | Thinned | 36.7 (7.5) | 15.2 (2.2) | 10 (6) | 173 (208) | PIPO (96%)<br>PSME (4%) |
| Red Feather | Untreated | 34.6 (12.5) | 11.8 (2.9) | 10 (8) | 353 (561) | PIPO (80%)<br>PSME (12%) |
| | Thinned and burned | 33.7 (10.2) | 11.6 (2.5) | 7 (4) | 141 (200) | PIPO (96%)<br>PSME (4%) |
| Dry Lakes | Untreated | 41.2 (10.5) | 12.2 (3.1) | 11 (8) | 534 (870) | PIPO (84%)<br>QUGA (12%) |
| | Thinned and burned | 37.2 (8.0) | 13.2 (2.6) | 11 (8) | 161 (121) | PIPO (98%)<br>QUGA (1%) |
| Sledgehammer Gulch | Untreated | 34.7 (9.8) | 12.1 (2.9) | 16 (9) | 670 (1100) | PIPO (72%)<br>POTR (13%) |
| | Thinned and burned | 33.5 (12.0) | 12.6 (4.0) | 6 (4) | 554 (1520) | PIPO (83%)<br>POTR (11%) |

QMD, quadratic mean diameter; TH, mean tree height; BA, Basal area; PIPO, Ponderosa pine; PIED, two needle pinyon; PSME, Douglas-fir; POTR, quaking aspen; QUGA, Gambel oak

Three of the six sites were mechanically thinned with treatments designed to reduce crown fire hazard and restore forest structure to conditions within historical ranges of variability by removing ladder fuels, incorporating openings, leaving clumps of trees, and preferentially retaining older trees (Kaufmann et al. 2001; Hunter et al. 2007). These sites are hereafter referred to as thinned sites. Each treatment on thinned sites was completed within three years prior to sampling. The three thinned sites were located in Heil Valley Ranch in Boulder County Open Space near Hygiene, Colorado, Bluewater in the Mount Taylor district of the Cibola National Forest in northwestern New Mexico, and Messenger Gulch in the South Park district of the Pike and San Isabel National Forests (Figure 1.1, Table 1.1).

At the remaining three treated sites, treatments were designed primarily to reduce fire hazard without an explicit goal of restoring the forest structure and consisted of a mechanical treatment followed by a broadcast burn. These treatments are hereafter referred to as thinned and burned sites. The treatments on thinned and burned sites were completed between 6 and 8 years before sampling occurred. The three thinned and burned sites were Red Feather in the Canyon Lakes district of the Arapaho and Roosevelt National Forests, Dry Lakes in the Tres Piedras district of the Carson National Forest, and Sledgehammer Gulch in the South Park district of the Pike and San Isabel National Forests (Figure 1.1, Table 1.1).

*1.2.2 Fuel Sampling Methods*

To determine the spatial autocorrelation of fuels in the surface fuel layer we utilized a 9 hectare nested cluster sampling design at each site to estimate fuel loading within surface fuel types and components (Figure 1.2, Table 1.2). The inventory was designed to provide multiple samples across a range of distances, informed by the results of Keane et al. (2012a), to provide inputs to spatial statistical models (see *Data Analysis*). The overstory and 1,000-hr fuels were sampled on 41 macroplots distributed across the site at variable densities (n = 41 per site). This included variable-radius plots using either a 2.3 or 4.6 BAF in order to characterize site-level

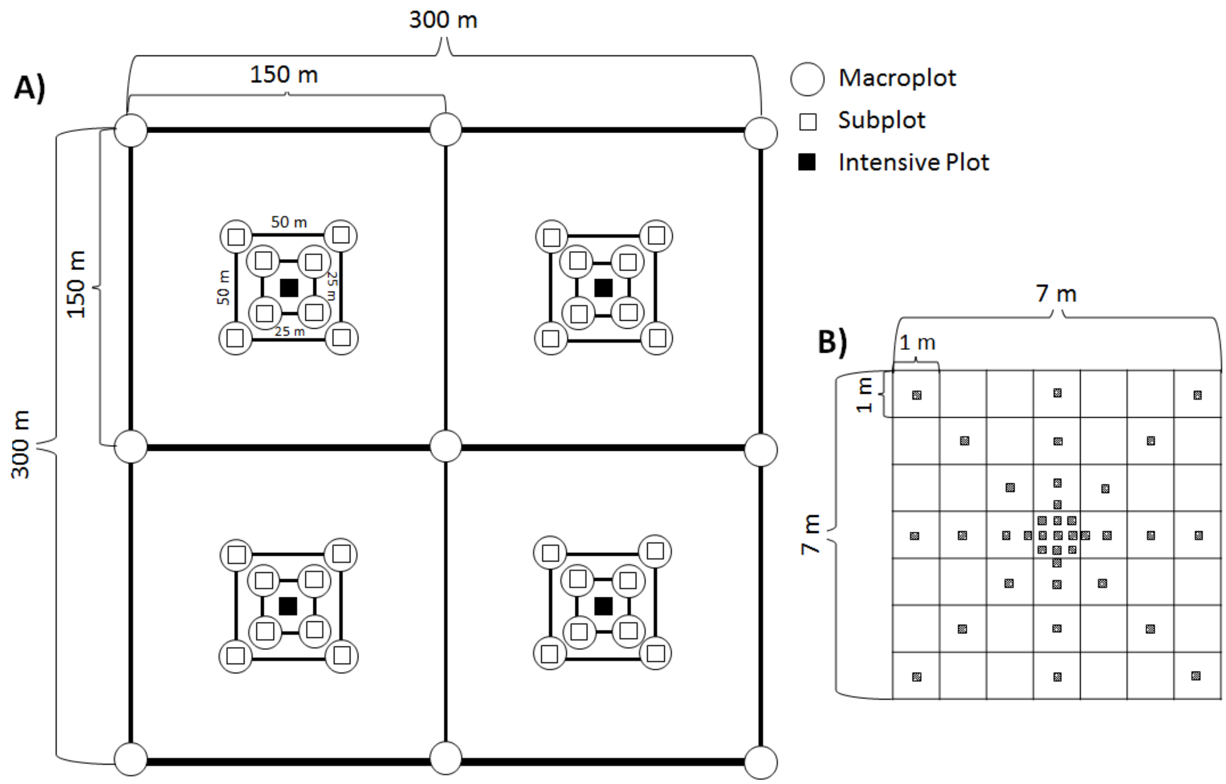


***Figure 1.2***: *Each site was inventoried using a nested cluster sampling design (A) that included 41 macroplots, 32 subplots, and 4 intensive plots. At each macroplot variable radius plots were used to measure the overstory and 200 $m^2$ fixed radius circular plots were used to sample 1,000-hr fuels. Each subplot included a 1 $m^2$ quadrat for sampling live herbaceous and shrub and dead woody fuels and a 0.09 $m^2$ frame for sampling litter and duff. Within each 7 by 7 m intensive plot (B) live herbaceous and dead woody fuels were sampled in each 1 $m^2$ grid cell (n=49) and litter and duff were sampled within 0.09 $m^2$ frames (n=37). Resulting n = 41 overstory and 1,000-hr fuel samples, n = 228 live herbaceous and dead woody fuel samples, and n = 180 litter and duff fuel samples at each site.*

estimates of basal area, species composition, average tree height and crown base height, and stems per hectare and 200 $m^2$ fixed-radius plots for measuring 1,000-hr downed dead woody fuels. At each 200 $m^2$ plot species, decay class (sound or rotten), length (m), and end diameters (m) of each fuel particle was recorded; for particles extending outside of the fixed-radius plot diameters were collect at the plot edge and length was measured for the portion of the particle inside the plot. The volume of the fuel particle was then calculated as a conical frustum

(Equation 1), and multiplied by a species-specific density (Harmon et al. 2008) to create a loading estimate.

$$(1) \qquad V = \frac{1}{3}\pi(R_1^2 + R_1R_2 + R_2^2)$$

***Table 1.2*** *Description of the eight surface fuel types and components sampled in this study*

| Fuel type | Fuel component | Particle Size | Description |
|---|---|---|---|
| Downed dead woody | 1-hr | <0.64 cm (0.25 inch) diameter | Detached woody fuel particles on the ground |
| | 10-hr | 0.64-2.54 cm (0.25-1.0 inch) diameter | |
| | 100-hr | 2.54-7.62 cm (1-3 inch) diameter | |
| | 1,000-hr | >7.62 cm (3 inch) diameter | |
| Shrubs | Shrub | All sizes | Shrubby biomass |
| Herbaceous | Herb | All sizes | All live grass, forb, and fern biomass |
| Litter | Litter | All sizes excluding woody | Freshly fallen non-woody material |
| Duff | Duff | All sizes | Partially decomposed biomass |

Litter and duff fuel loads were measured on 0.09 $m^2$ plots located at the 32 subplot locations and from 37 locations within each intensive plot (Figure 1.2; n = 180 per site). Litter was defined as freshly fallen, readily identifiable non-woody plant necromass (Keane 2015) and includes the $O_i$ soil horizon (Schoeneberger et al. 2012). Duff was defined as the layer below litter and above mineral soil where necromass is partially decomposed and the original source of fuel particles is no longer easily identifiable (Keane 2015); this is equivalent to the remainder of the *O* horizon (Schoeneberger et al. 2012). Animal droppings and pinecones were excluded from litter and duff collections.

1-hr, 10-hr, and 100-hr downed dead woody fuel loadings were inventoried using photoload double sampling of 1 $m^2$ quadrats, with one located at each subplot and 49 in each intensive plot (Figure 1.2; n = 228 per site; Keane et al. 2007). In order to account for any visual estimation bias, downed dead woody material was extracted and sorted by time-lag size classes at a randomly selected 20% of plots ($n_{sub\text{-}sample}$=48 per site). As shown by Tinkham et al. (in press), a 20% double sampling rate provides substantial improvements to sample bias and precision of the mean. In cases where a fuel particle was only partially within the 1 $m^2$ plot only the portion within the sampling plot was collected. Using linear regression between the visual estimates and destructive samples a bias correction factor for each particle size, site, and observer combination was developed and applied to each visually estimated sample. Additionally, within each 1 $m^2$ quadrat standing live fuels below 2.0 m were clipped at the soil surface and classified as shrub or herbaceous fuels (Figure 1.2; n = 228 per site). All extracted litter, duff, 1-hr, 10-hr, 100-hr, shrub, and herbaceous fuels were placed in ovens at 70 °C until the measured weight stabilized and then dry weights were recorded.

*1.2.3 Data Analysis*

To characterize spatial variability and CLS of fuel loading in ponderosa pine forests of the southern Rocky Mountains we constructed individual semivariograms generated from all pairs of observations for each fuel component by treatment type following Webster and Oliver (2007) (Figure 1.3). Additionally a semivariogram was created for each treatment across sites with maximum separation distances set at 200 meters, increasing the amount of data at each lag distance without introducing interactions between sites.

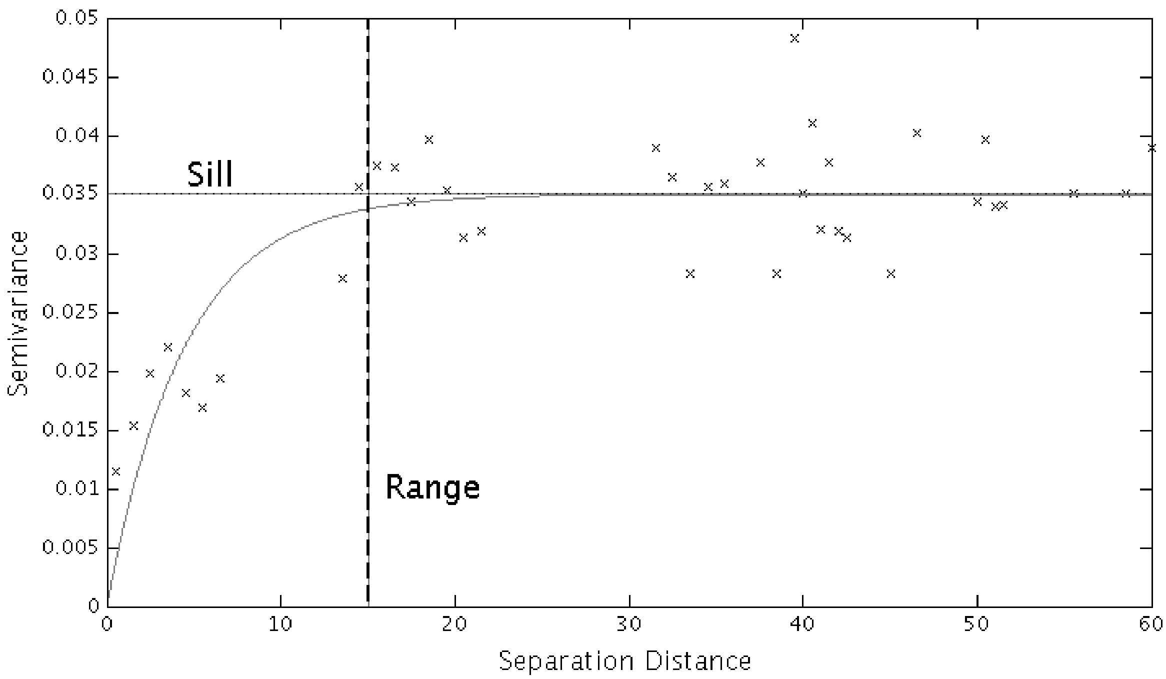


***Figure 1.3****: Elements of a semivariogram. The range is the separation distance at which the modeled curve flattens, and is an estimate of the characteristic length scale of a spatial process, representing the scale at which the process or characteristic is best described. The corresponding y-axis value along the modeled curve at the range is called the sill, and represents the maximum variation of the process.*

Semivariograms present a graphical representation of the spatial continuity of a dataset by calculating the variance of measured sample points as a function of their separation distance. We characterized our semivariogram models using three modeled variables: the range, the sill, and the nugget (Figure 1.3). The range was estimated as the point along the x-axis where the modeled curve flattens. Points located next to each other at scales below the range are spatially autocorrelated, while points spaced at distances larger than the range are spatially independent. The range value can thus be thought of as an estimate of the CLS of a spatial processes or characteristic of the system and represents the scale at which the process or characteristic is best described. The corresponding y-axis value along the modeled curve at the range is called the *sill*, and represents the maximum variation of a process or system. The sill is similar to traditional statistical variance estimates. The *nugget* is the value of the fitted semivariogram at zero distance; a nugget other than zero represents measurement error or spatial variation at distances smaller than the sampling interval. A ‘pure nugget’ model, or one in which the sill and range are equal to zero and the nugget is non-zero, is the result of a process that occurs at smaller scales than those measured, or one which displays no autocorrelation.

Once all pairs of locations were plotted, we fit exponential semivariograms to the data using maximum likelihood estimators using the GeoR and mvtnorm statistical packages in R (Ribeiro and Diggle 2012; Genz et al. 2014) and visually inspected the fitted models to ensure that isotropy assumptions were met (Prudhomme and Reed 1999, Webster and Oliver 2007). We assumed that the nugget was zero in all cases except where the fitted range value was significantly smaller than the shortest lag distance sampled ($\alpha = 0.05$). In these cases, the model was interpreted as a pure nugget model, with a range of zero and a nugget value equal to the fitted sill. This process provided estimates and standard errors for the parameters of the semivariogram model.

To test if the fitted range and sill values for each fuel type were equal across the three different treatments we used a two-sample Z-test (Equation 2) with a critical value ($\alpha$) of 0.05 using the fitted values and standard errors for CLS and semivariance. This test meets normality assumptions because maximum likelihood estimators are normally distributed and samples were independent from each other due to the distance between sites.

$$(2) \qquad Z = \frac{\widehat{\sigma_1} - \widehat{\sigma_2}}{\sqrt{(\widehat{SE_1^2} + \widehat{SE_2^2})}}$$

We also developed scaling factors, through power function regression (Equation 3), for all surface fuel components in order to identify scale-invariant relationships and relate spatial variability to more easily measured fuelbed attributes. Power functions provide two unique characteristics that make them ideal candidates for investigating scaling relationships. First, they are scale invariant, which means that a change in scale of the independent variable does not change the functional form of the equation (Gisiger 2001; Stanley et al. 2000). Secondly, they are considered to be universal and thus can help identify general principles that apply across a wide range of scales (Marquet et al. 2005). Relationships were developed using the fitted range as the dependent variable and surface fuel component size as measured by diameter as the independent variable.

$$Y = ax^b, \qquad (3)$$

where $x$ is the particle diameter, $Y$ is the fitted range, $a$ is a normalization constant, and $b$ is the scaling exponent. Litter diameter was estimated as 0.2 cm following Keane et al. (2012a). Diameters of 1, 10 and 100-hr downed dead woody fuel particle classes were estimated as the midpoint of the size classes, and 1,000-hr downed dead woody fuels were divided into three classes (7.6-11 cm, 11-16 cm, 16+ cm), of which the mid points were used in the analysis. Dividing 1000-hr fuels into three size classes created a more evenly distributed set of x-values and avoided a function driven by one outlying point for this size category. Additionally, we investigated the relationships between the semivariance of fuel loading and the mean fuel loading by size class using a power-law function as described in equation 3, with the semivariance in fuel loading as the dependent variable and mean fuel loading as the independent variable. This analysis follows Taylor's Law, which states the variance of a natural population is proportional to a power of the population mean (Taylor 1961).

## 1.3 Results

### *1.3.1 Total Fuel Load*

Across all treatment types litter and duff fuel components had the greatest fuel loads, comprising 78, 70, and 60% of total fuel loading for the untreated, thinned, and thinned and burned sites respectively (Table 1.3). Downed dead woody fuel components comprised the next largest proportion of total fuel loading across all sites, comprising 20, 29, and 35% of total fuel loading for the untreated, thinned, and thinned and burned sites respectively. Within the downed dead woody fuel components the mean fuel load tended to increase as a function of fuel diameter, with the 1,000-hr fuel component having the greatest fuel loads in all treatment types. 1-hr fuel loadings ranged from 0.036 to 0.049 kg $m^{-2}$, while 1,000-hr fuel loadings ranged from 0.286 to 0.400 kg $m^{-2}$. Shrub and herbaceous fuels had the lowest fuel load of any fuel components, comprising 2, 1, and 5% of total fuel load for the untreated, thinned, and thinned and burned sites, respectively. Herbaceous fuel loadings were the lowest across all treatment types, with mean fuel loadings of 0.023, 0.017, and 0.033 kg $m^{-2}$ for the untreated, thinned, and thin and burned sites respectively. Shrub fuels had the next smallest loading on the untreated (0.034 kg $m^{-2}$) and thinned only sites (0.005 kg $m^{-2}$) but were greater than the 1-hr downed dead woody fuel loading on thinned and burned sites.

***Table 1.3**: Mean and standard deviation of loading by fuel component and treatment type*

| **Fuel Component** | **Average Loading in kg $m^{-2}$ (standard deviation)** | | |
|---|---|---|---|
| **Time-lag class** | **Untreated** | **Thin** | **Thin and Burn** |
| 1-hr | 0.049 (0.081) | 0.047 (0.072) | 0.036 (0.055) |
| 10-hr | 0.123 (0.204) | 0.270 (0.421) | 0.118 (0.171) |
| 100-hr | 0.093 (0.234) | 0.249 (0.591) | 0.141 (0.310) |
| 1,000-hr | 0.400 (0.659) | 0.323 (0.482) | 0.286 (0.548) |
| **Total Woody** | **0.665** | **0.889** | **0.581** |
| Litter | 0.660 (0.854) | 0.378 (0.666) | 0.363 (0.418) |
| Duff | 1.973 (2.864) | 1.765 (2.284) | 0.618 (0.907) |
| **Total Ground** | **2.633** | **2.143** | **0.981** |
| Shrub | 0.034 (0.268) | 0.005 (0.026) | 0.054 (0.122) |
| Herbaceous | 0.023 (0.034) | 0.017 (0.065) | 0.033 (0.037) |
| **Total Live** | **0.057** | **0.022** | **0.087** |
| **Total Loading** | **3.355** | **3.054** | **1.649** |

Across all of the management scenarios, coefficients of variation were over 100% for all fuel components. Thinned and burned sites had lower coefficients of variation than those of untreated sites for all fuel components except for 1,000-hr downed dead woody fuels. Regardless of changes in fuel loading, thinned sites had coefficients of variation 10 to 15% lower than those of untreated sites across all downed dead woody fuel components. Shrub and herbaceous fuel types had the highest and widest range of coefficients of variation of all fuel types (225 to 788% for shrub fuels and 112 to 382% for herbaceous fuels).

Both fuel reduction treatment types reduced total fuel loads, although thinned sites had increased downed dead woody fuel loadings. Thinned sites averaged 33% greater total woody fuel loadings but 10 to 83% lower average herbaceous, shrub, litter, and duff fuel loadings than untreated sites (Table 1.3). Thinned and burned sites had total fuel loadings 51% lower than untreated sites, primarily due to an average 63% decrease in litter and duff loadings. However, shrub and herbaceous fuel loadings were greatest on the thinned and burned sites, with roughly a 50% increase over untreated sites.

*1.3.2 Spatial Variability*

The estimated semivariance for downed dead woody fuel size classes tended to increase with fuel diameter (Figure 1.4, Table 1.4), with thinned sites having higher semivariance than thinned and burned sites for all components except 1,000-hr fuels, where they were not significantly different. There was no clear pattern in semivariance between untreated sites and either treatment type in downed dead woody fuels. The estimated semivariance for litter and duff did not differ significantly between untreated and thinned sites, but were significantly lower on thinned and burned sites for both fuel components (Figure 1.4, Table 1.4). Within untreated sites semivariance of shrub fuels was larger than any other surface fuel component other than 1,000-hr fuels, however, in thinned and burned sites it was the second smallest of any fuel component indicating a more homogeneous distribution of shrubs on those sites (Table 1.4). Herbaceous fuels on thinned sites had the lowest estimated semivariance of any fuel component on thinned sites. Due to zero-heavy and extremely skewed data, we were unable to produce maximum likelihood estimates for shrub fuel semivariance on thinned sites or herbaceous fuel semivariance on untreated or thinned and burned sites.

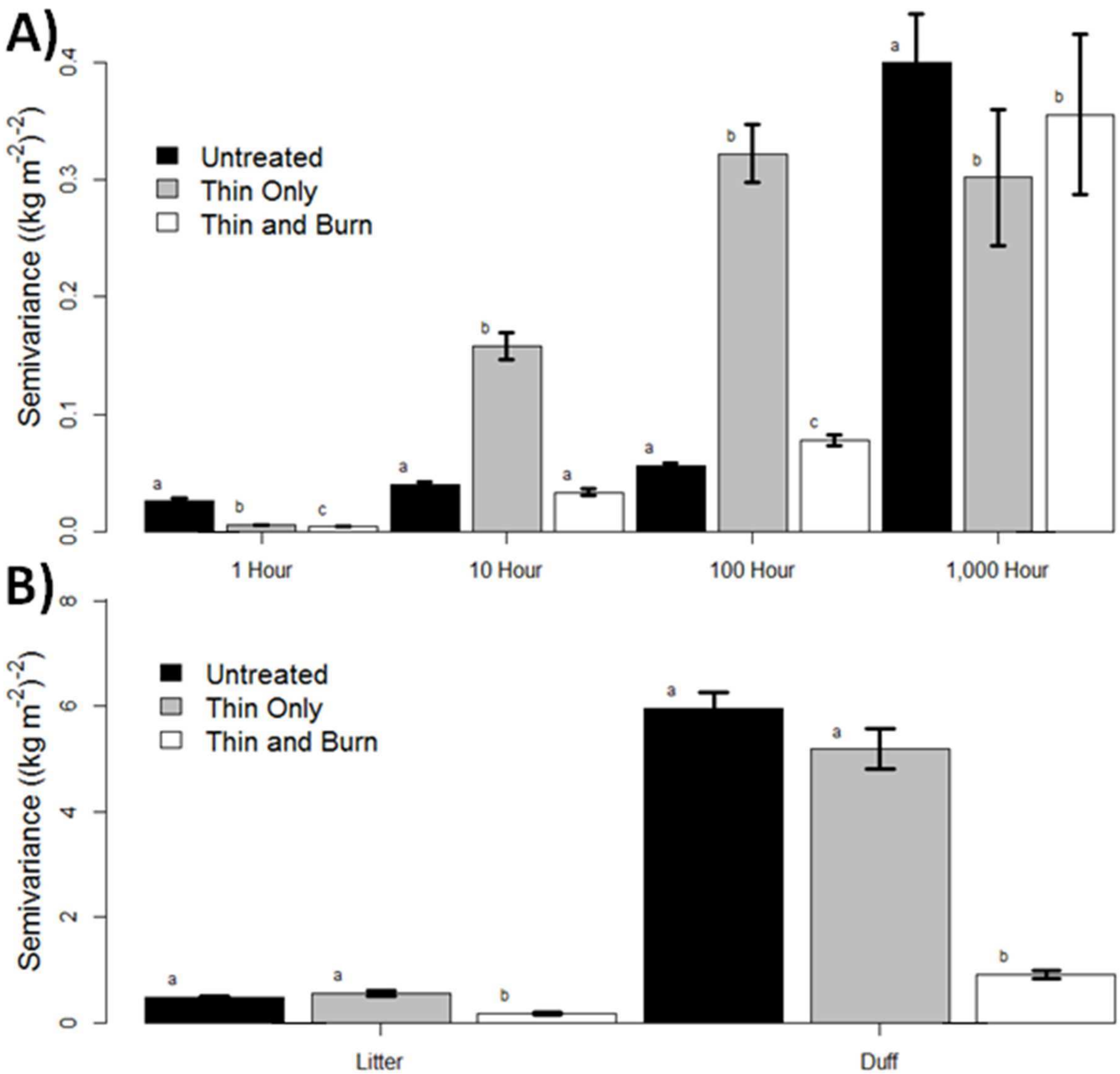


***Figure 1.4***: *Semivariance with standard errors for (A) downed dead woody fuels and (B) litter and duff fuels by treatment type. Letters represent significant differences (α = 0.05).*

***Table 1.4**: Variogram model fits by fuel component and treatment type. Values in parentheses represent standard errors.*

| Fuel Component | Rx | Sill $(kg\ m^{-2})^{-2}$ | CLS (m) |
|---|---|---|---|
| 1-hr | None | 0.0254 (0.0030) [a] | 14.50 (1.88) [a] |
| | Thin | 0.0054 (0.0003) [b] | 0.91 (0.11) [b] |
| | Thin and burn | 0.0041 (0.0003) [c] | 1.81 (0.22) [c] |
| 10-hr | None | 0.0403 (0.0022) [a] | 1.47 (0.11) [a] |
| | Thin | 0.1586 (0.0114) [b] | 1.32 (0.13) [a] |
| | Thin and burn | 0.0331 (0.0030) [a] | 1.44 (0.20) [a] |
| 100-hr | None | 0.0558 (0.0026) [a] | 0.89 (0.07) [a] |
| | Thin | 0.3226 (0.0249) [b] | 1.53 (0.15) [b] |
| | Thin and burn | 0.0777 (0.0051) [c] | 1.23 (0.10) [b] |
| 1,000-hr | None* | 0.3998 (0.0418) [a] | |
| | Thin | 0.3026 (0.0579) [a] | 47.59 (13.10) [b] |
| | Thin and burn | 0.3558 (0.0686) [a] | 46.89 (13.21) [b] |
| Litter | None | 0.4789 (0.0255) [a] | 1.13 (0.08) [a] |
| | Thin | 0.5518(0.0398) [a] | 0.93 (0.11) [a] |
| | Thin and burn | 0.1701 (0.0136) [b] | 0.99 (0.12) [a] |
| Duff | None | 5.9616 (0.3165) [a] | 1.18 (0.08) [a] |
| | Thin | 5.1888 (0.3857) [a] | 1.02 (0.10) [a] |
| | Thin and burn | 0.9112 (0.0744) [b] | 1.16 (0.13) [a] |
| Shrub | None* | 0.0717 (0.0002) | |
| | Thin** | | |
| | Thin and burn | 0.0133 (0.0008) | 1.00 (0.09) |
| Herbaceous | None** | | |
| | Thin* | 0.0041(0.0002) | |
| | Thin and burn** | | |

* Pure nugget model; value given in sill column is nugget value.
** MLE fit not possible due to distribution of data.

The CLS for surface fuel loading tended to increase with fuel component size, ranging from 0.9 to 47 m (Table 1.4). Litter, duff, shrub, herbaceous, and 1-, 10-, and 100-hr downed dead woody fuels all had CLS less than 4 m with the exception of the untreated 1-hr fuels, which had a CLS of 14 m (Figure 1.5). 1,000-hr fuels had CLS around 47 m for the thinned and thinned and burned sites and showed the greatest variability in CLS (Figure 1.5). We were unable to detect a CLS during our analysis of 1,000-hr fuels for untreated sites, producing a pure nugget model indicating that either the CLS is below 25 m or there is complete spatial randomness on these sites.

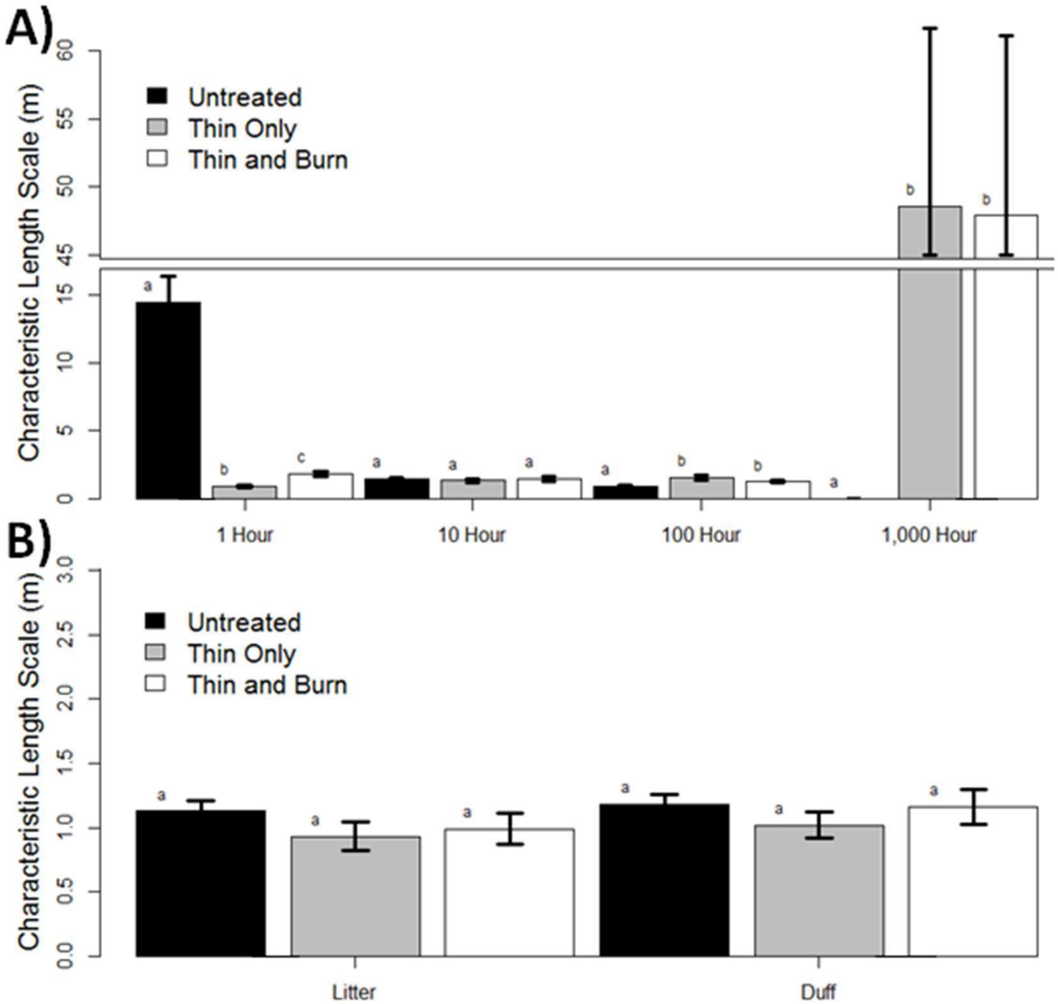


***Figure 1.5****: CLS values with standard errors of (A) downed dead woody fuels and (B) litter and duff fuels by treatment type. Letters represent significant differences (α = 0.05)*

Both treatment types resulted in a decreased CLS for 1-hr fuel loading from 14.5 m in the untreated sites to 0.9 and 1.8 m for the thinned and thinned and burned sites (Table 1.4; Figure 1.5). We found no significant differences among treatments in terms of the CLS for 10-hr fuels, which were approximately 1.4 m across all treatment types. Similarly, we found no differences in the CLS of duff or litter fuel loadings, which were approximately 1 m across all treatment types for both fuel components (Figure 1.5). In contrast, 100- and 1,000-hr fuels in both treatment types had significantly increased CLS relative to untreated stands, with CLS of 100-hr fuels in treated sites being between 1.4 and 1.7 times larger than untreated sites. If we assume a 1,000-hr fuel CLS of 25 m for untreated sites (pure nugget), which represents our lowest separation distance, we would conservatively estimate an approximately 1.9 fold increase in 1,000-hr fuel CLS for treated sites.

Shrub and herbaceous fuels were sparse with zero-heavy and extremely right-skewed data, and we were unable to fit a semivariogram for thinned shrub fuels and untreated and thinned and burned herbaceous fuels. Herbaceous fuels in thin-only sites produced a pure nugget model, implying that spatial autocorrelation occurred at scales small than our sample spacing of 1 m. Within the herbaceous and shrub fuel types the only comparison we were able to make was for shrub fuel loading in untreated and thinned and burned sites, where untreated sites produced a pure nugget model indicating spatial autocorrelation occurred at a scale smaller than the 1 m CLS of thinned and burned sites.

*1.3.3 Scaling Factors*

Regressions of CLS to fuel components particle size across treatments provided scaling factors for surface fuels, showing that CLS increased with fuel particles size. Using the scaling function given in Equation 3, the resulting fit was

$$(4) \qquad CLS = 0.217d^{1.839}$$

where *d* is the fuel particle diameter in cm ($R^2$= 0.879; Figure 1.6). This fit reflects the similar CLS values for smaller fuels and the large increases in CLS values of larger diameter fuels, and implies that on average 1-, 10-, and 100-hr fuels have CLS of 0.3, 0.5, and 4.3 m respectively, while particles 15 cm in diameter will have an average CLS of 31.6 m in ponderosa pine forests.

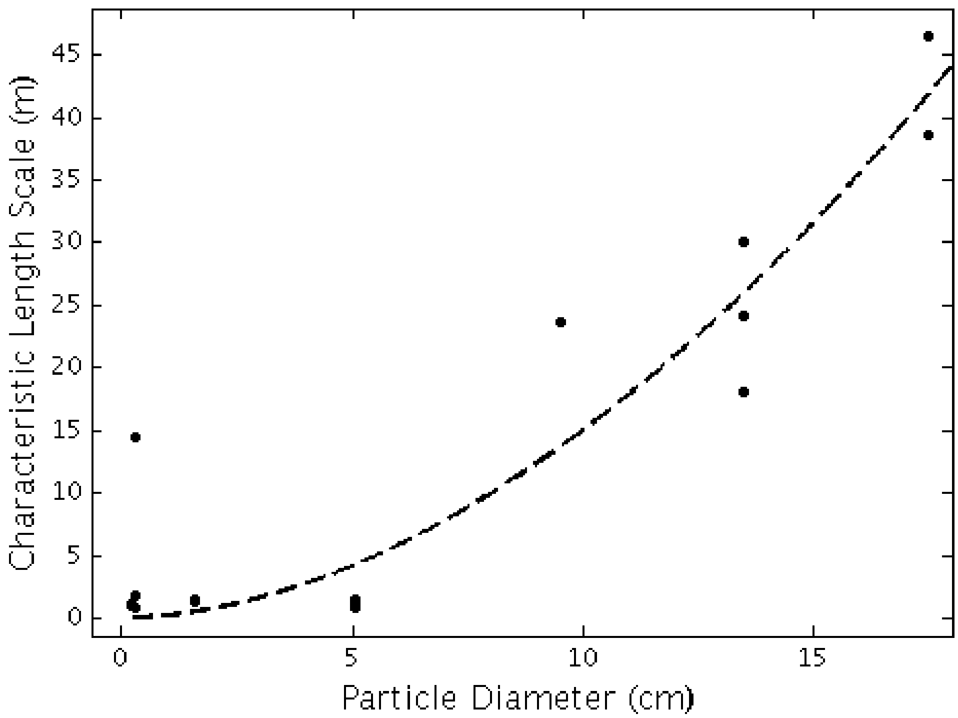


***Figure 1.6***: *Relationship between average particle diameter within each fuel component and characteristic length scale ($R^2$= 0.88).*

Regression analysis also showed that semivariance increased with site-level average fuel loading across all treatment types. Fitting the data to our scaling function (Equation 3) resulted in the equation

$$(5) \qquad Semivariance = 1.862 * load^{1.742}$$

where *load* is the fuel load in kg $m^{-2}$ ($R^2$ = 0.99; Figure 1.7). The scaling factor of 1.7 shows that the fuel load variability increases at a greater rate than average site-level loading and that a doubling of fuel load results in a 3.3-fold increase in variability.

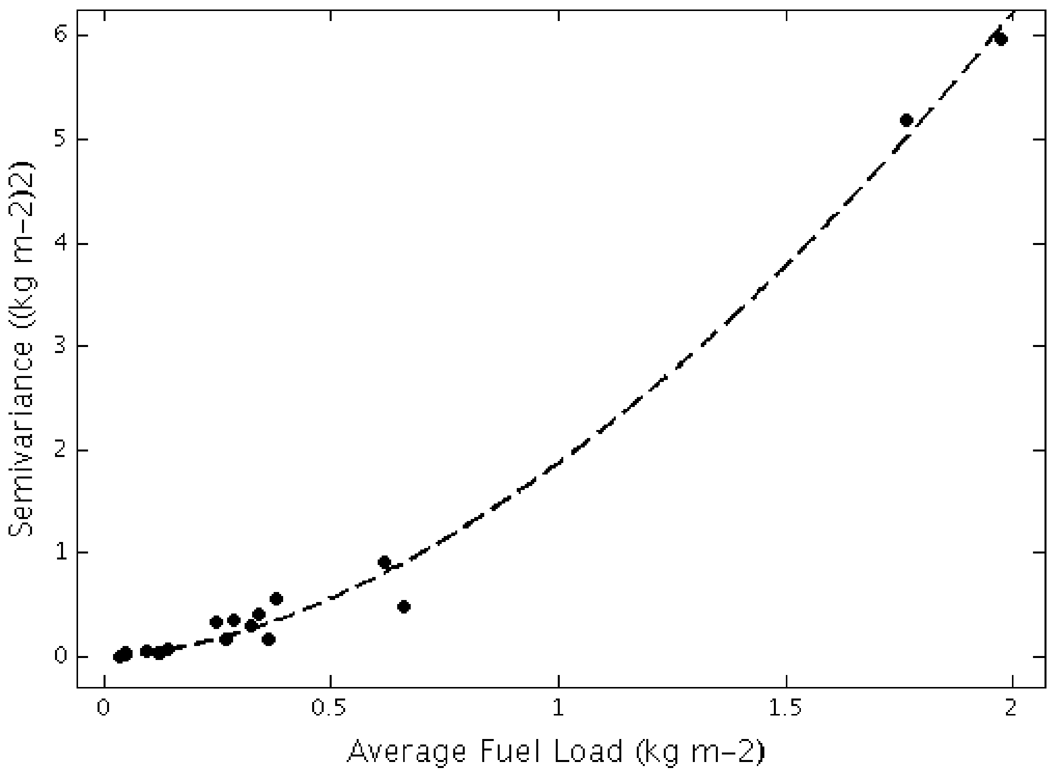


***Figure 1.7**: Relationship between average site-level fuel loading within each fuel component and semivariance ($R^2$= 0.99).*

## 1.4 Discussion

The study found that surface fuel loadings are highly variable across and within surface fuel types and components in ponderosa pine forests of the Southern Rocky Mountains regardless of the treatment type. We found similarly high variability for downed dead woody fuels to that found by Brown and Bevins (1986) and Keane et al. (2012a). However, we additionally showed that fuel-loading variability of litter, duff, herbaceous, and shrub fuels tended to be higher in ponderosa pine forests of the Southern Rocky Mountains than the Northern Rocky Mountains. These differences held across sites and treatment types, suggesting that regional differences in productivity or understory species composition, not recent management activity, may be the cause.

Both fuel reduction treatment types reduced total fuel loads and the relative amount of each fuel type. In particular, a markedly higher percentage of fuel loading was found in downed dead woody fuels on thinned and burned sites than in either of the other two management scenarios. Similar changes in fuel loading following prescribed burning have been found in ponderosa pine forests of western Montana in combination with mechanical treatments (Scott 1998) and in burn-only treatments in Arizona (Sackett 1980a). However, fuel loads in these cases tended to decrease by larger percentages across fuel components, particularly in terms of the 1,000-hr downed dead woody fuel component loading. Larger decreases in loading in other studies may be a result of burn objectives or of higher initial loadings leading to increased consumption during burning (Thaxton and Platt 2006). Similar patterns of change in fuel load following mechanical only and mechanical and prescribed fire treatments have also been found in conifer forests across the western United States (Stephens and Moghaddas 2005; Stephens et al. 2009).

Recognizing and accounting for spatial variability in measuring surface fuel loading can improve the ability of fuel loading measurements to meet their intended purposes of informing management decisions. For example, mean values across a stand may not be helpful in sampling downed dead woody material for wildlife habitat assessment when the wildlife species in question requires high densities of jackstrawed logs (Bate et al. 2004). Similarly, risk of spruce beetle outbreak in a stand is greatly increased by the presence of heavy fuel loads concentrated in small areas—a phenomenon that may not be captured by a simple stand-level mean (Reynolds and Holsten 1994). Thaxton and Platt (2006) and Hiers et al. (2009) have suggested that incorporating true scales of surface fuel variability into fire modeling rather than using stand-level means may be an important step in linking fire behavior and effects to fuel loadings.

Collecting meaningful data on the spatial variability of fuel loading throughout a stand requires an understanding of the scale of that variability.

The CLS found in this study fall within the ranges of CLS for the fuel components reported for three north Rocky Mountain ponderosa pine sites in Keane et al. (2012b), but are greater than those reported by Hiers et al. (2009) for longleaf pine dominated stands. Regardless of any differences in CLS and semivariance found between these studies, there is mounting evidence that surface fuel loadings of all but the largest fuel components are highly variable at scales below 20 m, and often closer to 1 m. These findings suggest that typical sampling plot sizes of 0.04 to 0.09 ha are too large to capture the system dynamics of fuels complexes, and that smaller plot sizes are needed to improve fuels sampling to achieve a detailed picture of fuel distributions. In addition, our results showed that fuel reduction treatments differentially effect the spatial distributions of different fuel components, signifying that optimal sampling scales may change with management practices.

Knowing the scaling relationships that relate spatial distributions to more readily measured variables such as mean loading and particle diameters can contribute to improving sampling designs that incorporate spatial variability. The two measures of spatial variability we analyzed (CLS and semivariance) showed strong predictability by either fuel particle diameter or stand-level mean fuel loading, variables that are more easily measured, require fewer samples to accurately characterize, and less post-processing of field-collected data. For example, 1-, 10-, and 100-hr fuels could be rapidly sampled using photoload estimation of quadrat clusters to capture spatial dynamics (Keane & Grey 2013; Tinkham et al. in press). If a particular precision is desired for a mean fuel load estimate, previously measured mean fuel loads could be used to predict the semivariance and inform the sample size required.

Although strong relationships were found between fuel components and the effect of fuels treatments on fuel spatial variability, certain limitations in the study design may have influenced specific results. Due to the intensive, time-consuming nature of the sampling design needed to characterize spatial variability, only a limited number of sites and treatment techniques could be assessed potentially limiting the inference of the results and preventing the separation of thin-only and burn-only treatments. Furthermore, due to the difference in time since treatment between the two treatment scenarios, some of the results in herbaceous and shrub fuel loading variability may result from the difference in time for the fuels complex to redevelop, although these are slow developing, low productivity systems. Further research that quantifies changes in the spatial scale and variability of fuels following treatments is needed, especially towards understanding the temporal development of fuels complexes and their implications on fuel treatment longevity.

# CHAPTER 2: FUEL PARTICLE DIAMETERS FOR IMPROVED FUEL LOADING ESTIMATES OF SOUTHERN ROCKY MOUNTAIN PONDEROSA PINE FORESTS

## 2.1 Introduction

Downed dead woody fuel loading is an important input to many fire behavior and effects models, and is an important indicator of the success of fuel hazard reduction treatments (Keane et al. 2012b). Many sampling techniques have been developed to estimate downed dead woody fuel loading in fire management, but the most widely used is the planar intersect method developed by Van Wagner (1968) and operationalized by Brown (1971, 1974). This method is often used in fuel inventories in part because it is relatively simple and quick to implement in the field and is easily taught to fire managers (Sikkink and Keane 2008). Rather than directly measure the fuel load this technique makes use of fuel particle counts of downed dead woody biomass within size classes that correspond to the moisture time lag classes used in the National Fire-Danger Rating System: 1-hr (0- 0.63 cm), 10-hr (0.63 -2.54cm), and 100-hr (2.54 – 7.62 cm) fuels (Deeming et al. 1972). These counts are multiplied by a slope correction factor and species-specific estimates of particle angles, specific gravity, and mean squared diameters ($d^2$) for each size class to calculate fuel loading.

However, due to differences in climate, branch growth patterns, and management practices, these estimates vary across broad geographical regions, by species and with stand management history (Brown and Roussopoulos 1974; Sackett 1980b). Stand management history including harvest practices, mastication, and prescribed burning can influence diameter distributions by selectively targeting certain sited material for removal, or through the preferential consumption of smaller diameter fuels. Previous studies have shown that improved estimates of particle diameters result in more accurate estimates of fuel loading (Keane and Gray 2013). Regional estimates of $d^2$ of 1-hr, 10-hr, and 100-hr fuels for common species are available for the Northern Rocky Mountains (Brown and Roussopoulos 1974), the Pacific Northwest (Ryan and Pickford 1978), and the Southwest (Sackett 1980b). In addition, Woodall and Monleon (2010) used Forest Inventory and Analysis data to provide national estimates by forest type and Brown (1974) provided a composite value for western tree species with no geographic specificity. These published $d^2$ values can vary by as much as 60% between regions for the same species. In addition to broad differences across geographic regions and species, $d^2$ is also affected by natural disturbances and management practices such as fire and harvesting. Most slash $d^2$ estimates were taken from clearcuts (Brown 1974), but clearcutting has become a more unpopular practice in dry forests of the southern Rocky Mountains and the Southwest in recent years. It is unclear how different silvicultural systems influence $d^2$ distributions and estimates, particularly in fine woody fuels.

The goal of this paper is to provide $d^2$ for downed dead woody biomass in ponderosa pine (*Pinus ponderosa*) stands on the eastern side of the continental divide in the Rocky Mountains of Colorado and New Mexico under three common scenarios: natural stands, stands that have been partially harvested to restore a more historic forest structure and composition, and stands that have been underburned after a partial harvest. Currently there are no published values of $d^2$ for the Southern Rocky Mountains, especially $d^2$ values that reflect the previously mentioned current silvicultural practices in these systems. The $d^2$ estimates provided in this study should improve downed dead woody fuel loading estimates produced using the planar intersect method in this region. In addition, we perform bootstrap analysis to determine the sample size required to produce reasonably accurate $d^2$ estimates at a local level. This analysis will inform the decision of whether to use published $d^2$ values or create locally specific values, a process Van Wagner (1982) theorized would require onerous amounts of extra fieldwork.

**2.2 Methods**

We collected downed dead woody fuels from 12 ponderosa pine-dominated stands on the eastern side of the continental divide across Colorado and New Mexico on the Roosevelt, Pike and San Isabel, Carson, and Cibola National Forests and in Boulder County Open Space. Overstory species composition ranged from 72% to 100% ponderosa pine by basal area, with other trees species including Douglas-fir (*Pseudotsuga menziesii*), quaking aspen (*Populus tremuloides*), and Rocky Mountain juniper (*Juniperus scopulorum*). Sampled stands ranged in elevation from 2000 to 2800 m, covering the elevational distribution of ponderosa pine forests in this region (Peet 1981; Dick-Peddie 1993), had slopes from 0 to 30%, and included all aspects. Because of the wide geographic and elevational range of sites sampled, the values presented here provide improved estimates of fuel loading with the planar intercept method for ponderosa pine dominated forests across New Mexico and Colorado east of the Continental Divide (Figure 2.1).

Six sampled stands had natural fuels, as they had not been subject to active management in the preceding thirty years. Three stands had been partially harvested using variable retention thinnings to reduce density and increase spatial heterogeneity to within the historic range of variation less than three years before sampling and three stands had been partially harvested and burned 6 to 8 years before sampling. Basal area was reduced by 8 to 68% in each treated area as compared to neighboring untreated stands. Our treatment sites thus differ qualitatively from those used in other studies (Brown and Roussopoulos 1974, Sackett 1980b, Bevins 1978) in that they were treated to reduce density and improve forest health while the other studies were conducted on stands where treatments emphasized timber harvesting. Harvesting, and particularly clearcutting, tends to remove more and larger trees from the site than forest health treatments do, therefore potentially leaving behind different amounts and distributions of fuels and overstory structures.

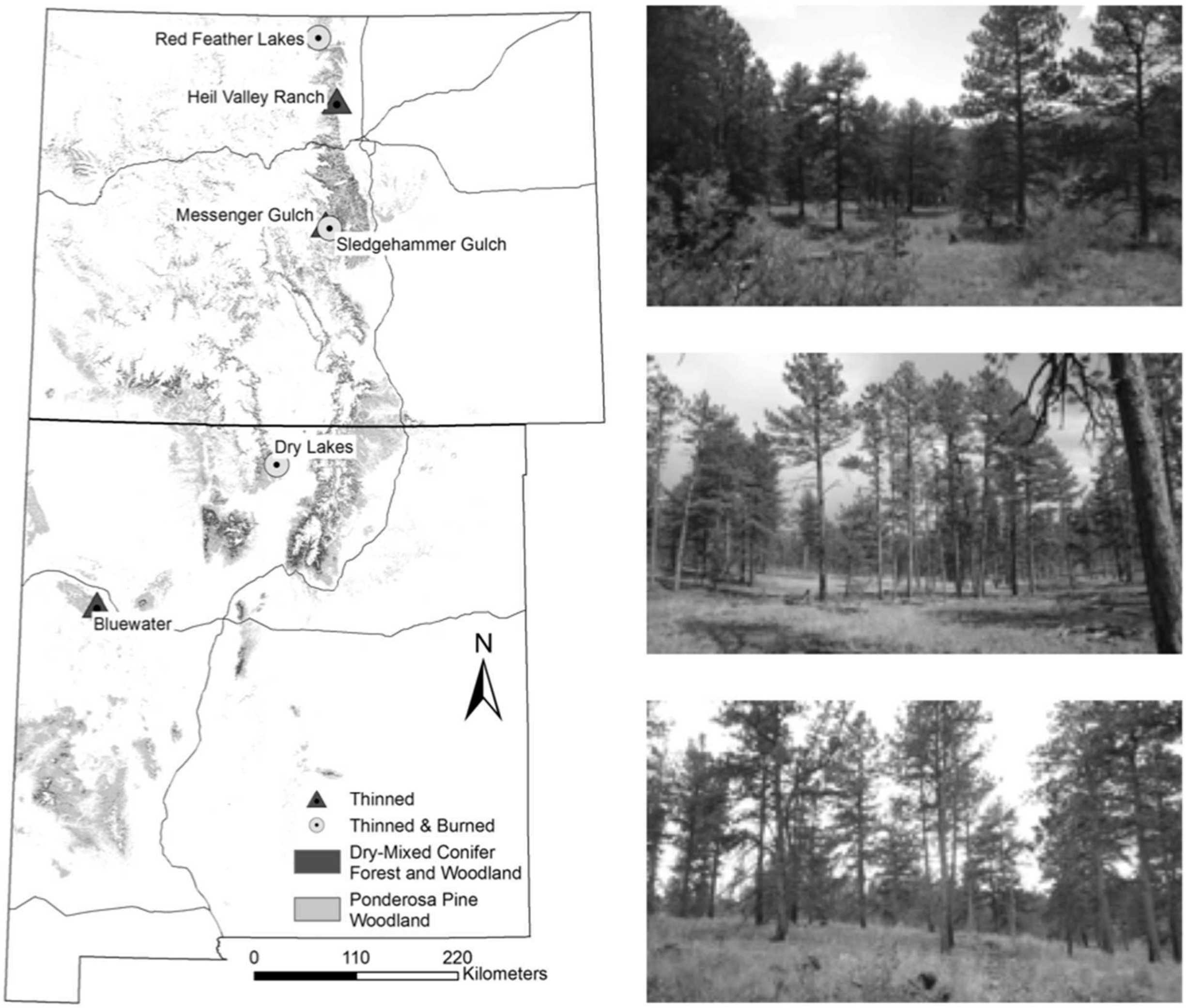


***Figure 2.1***: *Six ponderosa pine-dominated study locations across the southern Rocky Mountains used in this study. Each location contains an unmanaged site and a treated site. Thinned sites had received mechanical treatments designed to reduce crown fire hazard and restore forest structure. Thinned and burned site treatments were designed primarily to reduce fire hazard and consisted of a mechanical treatment followed by a broadcast burn. Images from top to bottom show examples of an untreated site, a thinned site, and a thinned-and-burned site.*

At each stand we randomly located a 9-hectare plot such that it was completely contained within the treatment unit and had an average slope of less than 5%. Within each quarter of the plot we randomly placed 12 1-$m^2$ frames for a total of 48 per site and collected all woody fuels less than 7.62cm in diameter. Because Brown (1974) requires the user to directly measure the diameter of 1000-hr fuels and calculate the $d^2$, they were not included in this study. Following woody fuel collection at each site we sorted all fuel into timelag classes (i.e. 1-hr, 10-hr, and 100-hr fuel classes), with fifty particles randomly selected from each timelag class and measured for endpoint and midpoint diameters. These measurements were used to calculate an arithmetic mean diameter for each particle and a stand-level quadratic mean diameter for each timelag class. From the stand-level quadratic mean diameters of each timelag class the arithmetic mean was calculated and squared to produce our $d^2$ estimate within each stand condition. Due to initial misclassifications of size class or low fuel loadings, in some cases sample sizes were less or more than 50 on a given site, but always at least 26 in each time lag class, which is sufficient to invoke the central limit theorem and thus provide an unbiased estimate of the mean (Ott and Longnecker 2010). Differences in the mean squared average quadratic diameter among different treatment types were tested using a generalized linear mixed model with treatment as a fixed effect, site as a random effect, and a random residual effect for each site to account for variance heterogeneity between treatments with a critical value ($\alpha$) of 0.05. The assumed response distribution was lognormal.

We used standard with-replacement bootstrapping techniques (Efron and Tibshirani 1993) to estimate the optimal sample size required to create accurate local estimates of $d^2$ for each size class and treatment combination. For each fuel size class and treatment combination we created 1000 bootstrapped samples ranging in size from 5 to 200 samples in increments of 5 and calculated the variance between the mean $d^2$ of each of the 1000 bootstrap observations at each sample size. For each fuel class and treatment type we visually evaluated changes in the $d^2$

variance across the range of sample sizes to determine the point where the decrease in variance was minimal compared with the increase in sample size (Jalonen et al. 1998). We considered the recommended sample size to be the visually estimated inflection point in the graph (Sikkink and Keane 2008).

## 2.3 Results

### *2.3.1 $d^2$ for Southern Rockies Ponderosa Pine Forests*

$D^2$ of 10-hr fuels did not differ significantly between natural, thinned, and thinned-and-burned groups ($p \geq 0.12$), while 1- and 100-hr fuels did have significant differences between untreated areas and at least one of the treatment types (Table 2.1). 1-hr $d^2$ in thinned-and-burned areas was significantly lower than untreated areas ($p < 0.0001$) and thinned areas ($p = 0.0213$). The 100-hr $d^2$ in thinned-and-burned areas was significantly lower than thinned plots ($p = 0.0041$), although thinned-and-burned plots did not differ significantly from natural plots

### *2.3.2 Required Sample Size*

We found that sample sizes of between 20 and 35 were optimal to determine $d^2$ for all cases based on the inflection points in our bootstrap analysis (Figure 2.2). The inflection point represents the sample size at which the decrease in variance from increasing the sample size is minimal compared with the time and effort required to accomplish the increased sample size (Sikkink and Keane 2008). Based on these findings we would conservatively recommend that at least 35 samples in each size class be collected to develop local $d^2$ estimates in ponderosa pine forests of the southern Rocky Mountains.

***Table 2.1*** *Regional d² estimates of downed dead woody fuel classes for ponderosa pine dominated forests. Significant differences within each size class of the Southern Rocky Mountain estimates are indicated by letters (α=0.05). This study's Thin estimates correspond to values reported as Slash in other publications. Differences between Southern Rocky Mountain estimates and other regional estimates are reported in parentheses. All estimates are given in cm².*

| Diameter Class (cm) | | Southern Rockies | Brown 1974[1] | Southwest[2] | Pacific Northwest[3] | National[4‡] |
|---|---|---|---|---|---|---|
| 0-0.63 | Natural | $0.268^{A}$ | 0.221 (-18%) | 0.244 (-10%) | 0.230 (-9%) | 0.053 (-80%) |
| | Thin | $0.258^{B}$ | 0.160 (-38%) | 0.304 (+18%) | - | - |
| | Thin and burn | $0.195^{C}$ | - | - | - | - |
| 0.63-2.54 | Natural | $1.746^{A}$ | 1.54 (-12%) | 1.53 (-13%) | 1.69 (-3%) | 1.56 (-11%) |
| | Thin | $1.871^{A}$ | 2.05 (+10%) | 1.59 (-15%) | - | - |
| | Thin and burn | $1.821^{A}$ | - | - | - | - |
| 2.54-7.62 | Natural | $15.698^{A}$ | 20.13 (+28%) | 19.16 (+22%) | - | 19.01 (+22%) |
| | Thin | $18.387^{B}$ | 18.26 (-7%) | 23.03 (+25%) | - | - |
| | Thin and burn | $14.778^{A}$ | - | - | - | - |

‡Numbers were estimated using a graphical estimation approach
[1]Brown 1974 [2]Sackett 1980b [3]Ryan and Pickford 1978 [4]Woodall and Monleon 2010

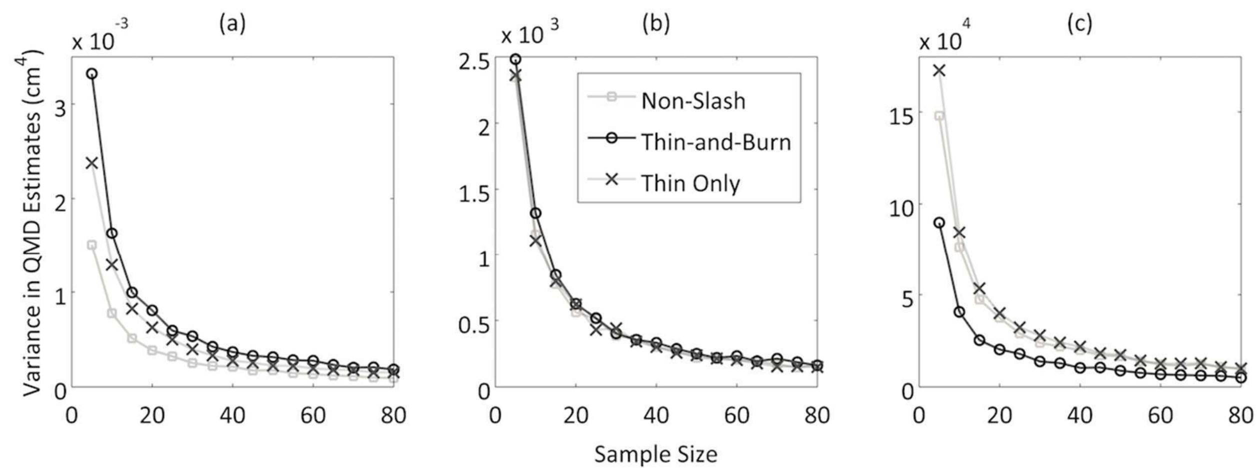


***Figure 2.2*** *Effect of sample size on the variance of sample d²*
Effect of sample size on the variance of sample d² for (a) 1-hour fuels (b) 10-hour fuels and (c) 100-hour fuels in ponderosa pine dominated forests in the Southern Rocky Mountains.

## 2.4 Discussion

Comparing our values to those reported for ponderosa pine from the Southwest (Sackett 1980b), the Pacific Northwest (Ryan and Pickford 1978), national values (Woodall and Monleon 2010), and those reported in Brown (1974) shows that our values generally result in greater estimates of the 1- and 10-hour timelag fuel loadings and a lower estimate of 100-hour timelag fuel loading (Table 2.1). These differences may be due to regional differences in climate, branch growth patterns, and common harvest or other management practices.

Overall our values show that total woody fuel estimates that use previously published $d^2$ values may capture the true total fine woody fuel loading in some cases because 1- and 10-hr fuel components would be overestimated while 100-hr fuels would be underestimated. However, estimates produced using previously published values are likely to result in inaccurate apportionment of fuel loading by size class in ponderosa pine forests of the southern Rocky Mountains. Errors in fuel distribution estimates are likely to be propagated through use in fire effects models and carbon storage estimates.

For any given fuelbed, loading estimates calculated using equations from Brown (1974) are directly proportional to the $d^2$ values used. For example, using a value ten percent higher for $d^2$ results in a ten percent higher estimate of fuel loading. In evaluating fuel treatment effectiveness within southern Rocky Mountain ponderosa pine forests, the $d^2$ values presented here would thus result in a sizeable increase in post-treatment fuel loading of 1- and 10-hr fuels compared to estimates using $d^2$ estimates from Brown (1974), assuming all other parameters in the model were held constant (Table 2.1). The $d^2$ values presented would also result in a 19% decrease in estimated 100-hr loading for thinned-and-burned sites compared to estimates using 100-hr slash values from Brown (1974). This suggests that it is worth considering thin-and-burn as a distinct disturbance category when choosing $d^2$ values in areas where treatments involve broadcast burning.

Our work also shows that contrary to the theorized effort requirements, within these ponderosa pine forests very few samples are needed to create local estimates of $d^2$. The recommended sample size of 35 can easily be collected and measured in under an hour using basic equipment, and the related calculations can be performed on a standard calculator, requiring no special software or expertise. While current $d^2$ values seem to capture total fine woody fuel loading, such an exercise would eliminate regional bias from the distribution of fuel loading within particle size classes.

Keane and Gray (2013) found that the accuracies of planar intersect-estimated fuel loads increased with better estimates of woody particle diameter measurements. However, there are several additional factors that may also contribute to uncertainty in fuel loading estimates with the planar intersect method. First, as suggested by Keane and Gray (2013) assumptions regarding the shape of woody fuel particles may be oversimplified, diameters may not be static through time, and common measurement techniques may not be appropriate. Second, other parameter estimates beyond the scope of this study, including specific gravity and particle angle, also influence fuel load estimates using the planar intersect method. Finally, the design of many common planar intersect sampling protocols fail to take into account the spatial variability of fuel loading itself (Keane et al. 2012b). More research is needed to better characterize the broad geographic variability of these parameters, to understand changes over time, and to provide a more mechanistic understanding of the drivers of local variability in fuel particle paramenters. Improved sampling designs may be necessary to accurately capture this spatial and temporal variability of surface fuels; however, the development of local $d^2$ estimates, such as done here, could provide a relatively simple approach that acts as a compromise between improving the accuracy of fuel estimates with the planar intersect approach and time and resource limitations for training and sampling using new methods.

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