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RESEARCH ARTICLE

Spatial scaling of wildland fuels for six forest and rangeland ecosystems of the northern Rocky Mountains, USA

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Abstract Wildland fuels are important to fire managers because they can be manipulated to achieve management goals, such as restoring ecosystems, decreasing fire intensity, minimizing plant mortality, and reducing erosion. However, it is difficult to accurately measure, describe, and map wildland fuels because of the great variability of wildland fuelbed properties over space and time. Few have quantified the scale of this variability across space to understand its effect on fire spread, burning intensity, and ecological effects. This study investigated the spatial variability of loading (biomass) across major surface and canopy fuel components in low elevation northern Rocky Mountain forest and rangeland ecosystems to determine the inherent scale of surface fuel and canopy fuel distributions. Biomass loadings (kg m^{-2}) were measured for seven surface fuel components—four downed dead woody fuel size classes (0–6 mm, 6–25 mm, 25–75 mm, and 75 + mm), duff plus litter, shrub, and herb—using a spatially nested plot sampling design within a 1 km^2 square sampling grid installed at six sites in the northern US Rocky Mountains. Bulk density, biomass, and cover of the forest canopy were also measured for each plot in the grid. Surface fuel loadings were estimated using a combination of photoload and destructive collection methods at many distances within the grid. We quantified spatial variability of fuel component loading using spatial variograms, and found that each fuel component had its own inherent scale with fine fuels varying at scales of 1–5 m, coarse fuels at 10–150 m, and canopy fuels from 100 to 500 m. Using regression analyses, we computed a scaling factor of 4.6 m for fuel particle diameter (4.6 m increase in scale with each cm increase in particle diameter). Findings from this study can be used to design fuel sampling projects, classify fuelbeds, and map fuel characteristics, such as loading, to account for the inherent scale of fuel distributions to get more accurate fuel loading estimations.

Keywords Wildland fire · Spatial variability · Biomass · Canopy fuel · Woody debris · Fuel loading · Scale

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Introduction

Most natural resource management and landscape ecology analyses use the mean of an ecosystem characteristic to represent that characteristic within a polygon or patch (Keane et al. 1998; Jensen and Bourgeron 2001). However, many biological and environmental variables are so highly variable in time and space that the mean often doesn't fully capture the influence, uncertainty, and importance of that characteristic across the landscape (Hunter and Price 1992). Daily precipitation, for example, is meaningless if the value is calculated as an average across a year because every day would have light rain (Berndtsson 1988). In ecology, it is often the variability of a characteristic across space that governs its impact and importance on ecosystems (Goldwasser et al. 1994), and nowhere is that more evident than in wildland fuel science.

Fuel properties, such as loading (Brown and See 1981), heat content (Van Wagtendonk et al. 1998), particle density (Harmon et al. 2008), size (Van Wagtendonk et al. 1996), and moisture (Agee et al. 2002), are amazingly variable in time and in space, and this variability has both direct and indirect influences on wildland fire effects and behavior. Fire spread, for example, is greatly influenced by the spatial distribution of fuels in three dimensions (Rocca 2009; Parsons et al. 2010); fine scale patches without fuels can dictate the direction, speed, and intensity of fire spread (Agee et al. 2000; Thaxton and Platt 2006; King et al. 2008). To assign average fuel values to large areas, such as frequently done when creating fuel maps (Keane et al. 2001; Reeves et al. 2009), ignores the extraordinary influence that fuel variability can have on wildland fire processes. In fire ecology, for example, it is often the uneven distribution and consumption of fuel across multiple scales that determine patterns of post-fire plant mortality, plant growth, and colonization dynamics (DeBano et al. 1998), yet impacts of this complex fuel patchwork are disregarded when managers assume uniform fuel distributions.

Wildland fuel is the one factor that can be directly manipulated to achieve management goals, such as restoring ecosystems, lowering fire intensity, minimizing plant mortality, and reducing erosion (Graham et al. 2004; Ingalsbee 2005; Reinhardt et al. 2008). As a result, comprehensive descriptions of fuels are needed in nearly every phase of fire management including fighting wildfires (Graham et al. 2004; Ohlson et al. 2006; Chen et al. 2006), implementing prescribed burns (Agee and Skinner 2005), describing fire danger (Deeming et al. 1977), and predicting fire effects (Ottmar et al. 1993; DeBano et al. 1998). Consistent and accurate fuel descriptions are critical inputs to the fire behavior and effects models that are used to plan, prioritize, design, and implement important fuel treatments that could save lives and property (Reinhardt and Keane 1998; Andrews 2008; Hessburg et al. 2010). Fuel loadings are also used to predict smoke emissions (Ottmar 1983; Hardy et al. 1999), quantify carbon pools (Reinhardt and Holsinger 2010), describe wildlife habitat (Bate et al. 2004), and evaluate site productivity (Hagan and Grove 1999; Brais et al. 2005; Woodall and Nagel 2006). Therefore, an accurate quantification of fuels and their variability is essential for most fire management analyses.

Wildland fuel components, however, are often difficult to measure, describe, and map for many reasons. A fuelbed can consist of many fuel components, such as litter, duff, logs, and cones, and the properties of each component, such as loading, mineral content, and moisture, can be highly variable, even within a single fuel particle, such as a twig, log, or grass blade (van Wagtendonk et al. 1996). Since each component is composed of different sized fuel particles, these properties can vary at different spatial scales (Habeeb et al. 2005). The within stand variability of fuel loading, for example, can be as high as the variability across a landscape, and this variability is different for each component, each fuel size, and each landscape setting (Brown and Bevins 1986, Keane 2008a). Fuel loadings are so highly variable that they often have poor correlations to vegetation characteristics, topographic variables, or climate parameters (Brown and See 1981; Rollins et al. 2004; Cary et al. 2006). It is the uneven distribution of fuel across space that confounds many fire management applications such as fuel classification, mapping, and fire behavior prediction.

The research presented here is a comprehensive effort to describe the spatial scale of variability of fuel loading for six common forest and rangeland ecosystems in the northern Rocky Mountains. We measured loadings for important fuel components within a large grid to describe their variability across several spatial scales using geostatistical techniques. We then related

Table 1 Descriptions of the three canopy fuel characteristics and the seven surface fuel components sampled in this study

Fuel component	Fuel component variable name	Common name	Size	Description
Canopy fuels				
All canopy fuels	CFL	Canopy Fuel Loading (kg m^{-2})	All dead and live biomass less than 3 mm diameter above 2 m	Biomass per unit area of the burnable crown fuel
	CBD	Canopy Bulk Density (kg m^{-3})	All dead and live biomass less than 3 mm diameter above 2 m	Maximum bulk density of the canopy for the burnable crown fuel across all 1 m layers
	CC	Canopy cover (%)	All dead and live biomass less than 3 mm diameter above 2 m	Vertically projected canopy cover of the canopy fuels
Surface fuels (loading, kg m^{-2})				
Downed dead woody	1 h	Twigs	<1 cm (0.25 inch) diameter	Woody fuels that are disconnected from parent plants and lying on the fuelbed within 2 m of the ground
	10 h	Branches	1–2.5 cm (0.25–1.0 inch) diameter	
	100 h	Large Branches	2.5–7 cm (1–3 inch) diameter	
	1,000 h	Logs	7 + cm (3 + inch) diameter	
Shrubs	Shrub	Shrubby	All shrubby material less than 5 cm in diameter	All burnable shrubby biomass with branch diameters less than 5 cm
Herbaceous	Herb	Herbs	All sizes	All live and dead grass, forb, and fern biomass
Duff	Duff	Duff	All sizes	Partially decomposed biomass whose origins cannot be determined
Litter	Litter	Litter	All sizes excluding woody	Freshly fallen non-woody material which includes needles, leaves, cones, pollen cones

We combined the duff and litter layer together in this study because it was often difficult to distinguish between the two layers

spatial variability statistics to fuel component sizes to scale fuel properties across space and compared these statistics across the sites. A companion paper addresses the variability of other fuel properties: particle density, bulk density, and mineral content, but also presents additional detail on the methods and results used in this study (Keane et al. 2012, in press). Results from this study have important implications for fire management in that they show that many conventional fuel sampling techniques, fuel classifications, and map products may be limited for certain applications, and that fuel science technologies need to incorporate fuel loading variability in their design.

Background

Wildland fuel is defined here as the organic matter available to foster fire ignition and sustain combustion (Albini 1976; Sandberg et al. 2001). The fuelbed is composed of basic elements called fuel particles that are grouped into fuel components based on size, type, and condition (Table 1). *Surface fuel* is the biomass within 2.0 m vertical of the mineral soil surface and is often divided into duff and litter, downed and dead woody biomass in a range of diameter classes, and live and dead standing vegetation (Table 1). Downed dead woody fuel is commonly separated into four components (Table 1) based on the diameter size classes required by fire behavior prediction systems (Andrews 2008). Each surface fuel component is often described by a unique set of characteristics for their use in fire management. *Fuel loading* is defined as the mass of a fuel component per unit area (kg m^{-2}) and it is the only characteristic evaluated in this paper. The density of woody fuel particles (*particle density*, kg m^{-3}) is the mass per unit volume of fuel particles, which is a function of the species, particle size, and degree of decay. Particle density is a major parameter that we used to determine fuel loadings. *Bulk density* is the amount of biomass per unit volume measured as the mass of a fuel component(s) in the volume that defines the fuelbed (Brown 1981). This volume is usually estimated as a unit area times the height of the fuelbed. We used the bulk densities of the litter, duff, shrub, and herb fuelbed components to estimate their loadings.

Canopy fuel is burnable aerial biomass that is higher than 2.0 m above the ground, and consists primarily of branches and foliage, but also includes arboreal mosses, lichens, dead ladder fuels, and other hanging dead material such as dead needles and branches (Reinhardt et al. 2006). Many fire behavior prediction systems do not differentiate between canopy fuel components because of the low resolution of crown fire models (Rothermel 1991) and the minor influence that large canopy fuel has on crown fire behavior (van Wagner 1977). As a result, canopy fuel is often only described by the biomass that can be burned in a crown fire, defined in this study as all canopy material less than 3 mm in diameter (Call and Albini 1997). This burnable canopy biomass, when summed over a unit area, is called the *canopy fuel loading* (CFL, kg m^{-2}). Since the remaining coarse canopy material (greater than 3 mm diameter) rarely burns in a wildfire or prescribed fire, it is often ignored in fire models, yet this material is fundamentally important in carbon dynamics (Finkral and Evans 2008; Reinhardt and Holsinger 2010). *Canopy bulk density* (CBD, kg m^{-3}), defined as the mass per unit volume of burnable canopy biomass (again, foliage and twigs less than 3 mm in diameter), is perhaps the most important canopy fuel property (van Wagner 1977; Alexander 1988), but it is also the most difficult to measure because it requires detailed knowledge of the vertical distribution of crown biomass (Alexander 1988) and there are few standardized field methods for estimating CBD. The most popular method for estimating CBD involves using measurements of tree diameter, height, and crown base height for all trees in a plot to calculate crown biomass distribution from allometric crown biomass equations (Reinhardt et al. 2006).

Fuel variability

Spatial variability has been assessed for ecophysiological attributes (Rodeghiero and Cescatti 2008), soil properties (Grunwald et al. 2007), weather variables (Augustine 2010), hydrological parameters (Russo and Bouton 1992), and vegetation characteristics (Powell and Hansen 2007). However, few studies have directly assessed the spatial variability of wildland fuels. Kalabokidis and Omi (1992) used quadrats to assess spatial variability of sagebrush ecosystems to determine optimal sampling strategies. Reich et al. (2004) evaluated the coarse-scale (30 m) spatial variability of several fuel components for a large landscape in the Black Hills, USA by modeling fuel properties from remote sensing products and found that the variability was correlated to topography and vegetation, but they did not evaluate the inherent scale of this variability or spatial variability at finer scales (<5 m) across fuel components. Hiers et al. (2009) measured small scale variations in fuel heights that were quantified using LIDAR and found that these heights were spatially independent after small lag distances (0.5 m^2). Parsons et al. (2010) simulated fine scale variations in fuel characteristics for a small area using the FUEL3D program and input these fuel distributions into highly mechanistic computational fluid dynamics models. Spatial variation of grasslands have been described in the context of population dynamics and restoration potential (Thorhallsdottir 1990; Peters et al. 2006) and fuel loadings have been manipulated at fine scales (1–5 m) to investigate the influence of fine fuel mosaics on fire intensity and effects (Thaxton and Platt 2006; Rocca 2009). Several studies have described the patterns of fuel distributions across the landscape, but few have actually quantified the variability of fuel properties across space (Miller and Urban 2000; Jia et al. 2006; Kennedy et al. 2008; King et al. 2008). Van Mantgem and Schwik (2009) found insignificant spatial autocorrelation for a number of stand and surface fuel characteristics, but their 50 m sampling grid was probably too coarse for describing variability in finer fuels.

Spatial variability is often described using the *semivariogram* that graphically represents the spatial continuity of a data set (Bellehumeur and Legendre 1998; Townsend and Fuhlendorf 2010). The semivariogram depicts the spatial autocorrelation of measured sample points. Once each pair of locations is plotted, a model is fit through them. Unique semivariogram characteristics are commonly used to describe spatial variability (Fig. 1). Theoretically, at zero distances, the semivariogram intercept value is zero, but, most semivariograms exhibit a *nugget* effect

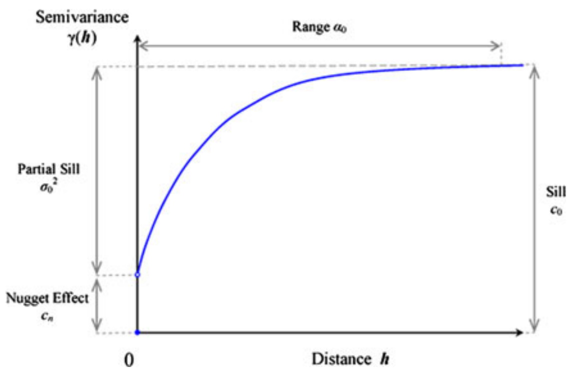

Fig. 1 Important characteristics of a semivariogram. The nugget, sill, and range are commonly used to describe the spatial variability of an ecological characteristic. From the SAS/STAT(R) 9.3 Users Guide (http://support.sas.com/documentation)

(intercept values greater than zero) that is often attributed to measurement errors or spatial sources of variation at distances smaller than the sampling interval (or both). Natural phenomena, such as fuels, can vary spatially over a wide range of scales and the distance where the curve first flattens is known as the *range*; sample locations separated by distances closer than the range are spatially autocorrelated, whereas locations farther apart are not. Semivariogram range is important in ecology because it represents the scale at which the entity is best described in space or the "inherent" scale. The value of the semivariogram model at the range is called the *sill* (Townsend and Fuhlendorf 2010), and it represents the maximum variation on the landscape.

Methods

Study sites

Six study sites were selected for sampling after extensive GIS analyses and field reconnaissance (Fig. 2; Table 2). We targeted the most common mature forested and rangeland vegetation types in the northern Rocky Mountains, but these areas had to be (1) homogeneous with respect to vegetation and topography, (2) large with at least 2.0 km^2 in area to accommodate large sampling grids, (3) flat with less than 10 % slope to minimize the influence of slope on woody fuel alignment, and (4) accessible within at least 1 km of a road. Few contiguous, homogeneous areas met our criteria, especially for high elevation forests and forested ecosystems that are rare on the landscape. As a result, we sampled only low-elevation semi-arid and temperate ecosystems (Table 2). We could not replicate our sampling for the same ecosystem type because of the rarity of potential sampling sites in the US northern Rocky Mountains.

The first site sampled was in University of Montana's Lubrecht State Forest (Lubrecht Forest, LF) in west-central Montana (Fig. 2; Table 2)—a second-growth dry mixed conifer stand of ponderosa pine (*Pinus ponderosa*), Douglas-fir (*Pseudotsuga menziesii*), and western larch (*Larix occidentalis*) that had been thinned approximately nine years prior to sampling so some residual down woody fuels were still present on the site. The ponderosa pine-Douglas-fir stand on the Ninemile Ranger District of the Lolo National Forest (Ninemile, NM) was on a gentle (<10 %) south-east facing slope in the Douglas-fir/ninebark habitat type (Pfister et al. 1977) that had a prescribed burn implemented approximately eight years prior to sampling. The Tenderfoot Forest (TF) site is on the Tenderfoot Creek Experimental Forest in the Lewis and Clark National Forest in central Montana and was composed of an open lodgepole pine overstory with a history of non-lethal surface fires and an understory fuelbed that consists primarily of low grouse whortleberry (*Vaccinium scoparium*) shrubs with scattered downed woody fuels. The Silver Mountain (SM) site is an open pinyon pine (*Pinus edulis*) and juniper (*Juniperus occidentalis*) woodland with woody scattered fuels, sparse sagebrush shrubs, and frequent bare soil and gravel patches. The Colville Forest (CF) site was a ponderosa pine savanna with a rough fescue (*Festuca scabrella*) undergrowth and thickets of Douglas-fir trees scattered in a matrix of widely spaced ponderosa pine trees that had been thinned in a 2007 fuel treatment to reduce crown fuels.

Field measurements

Canopy and surface fuels were sampled differently in this study because of methodological, logistical, and scale issues (Scott and Reinhardt 2002; Reinhardt et al. 2006). Only loadings for those surface fuel components described in Table 1 were sampled in this study because they are common inputs to fire models. Loadings for other fuel components, such as stumps, squirrel middens, and animal scat, were not included because these components were rare on the landscape, had no standardized sampling methods, and were

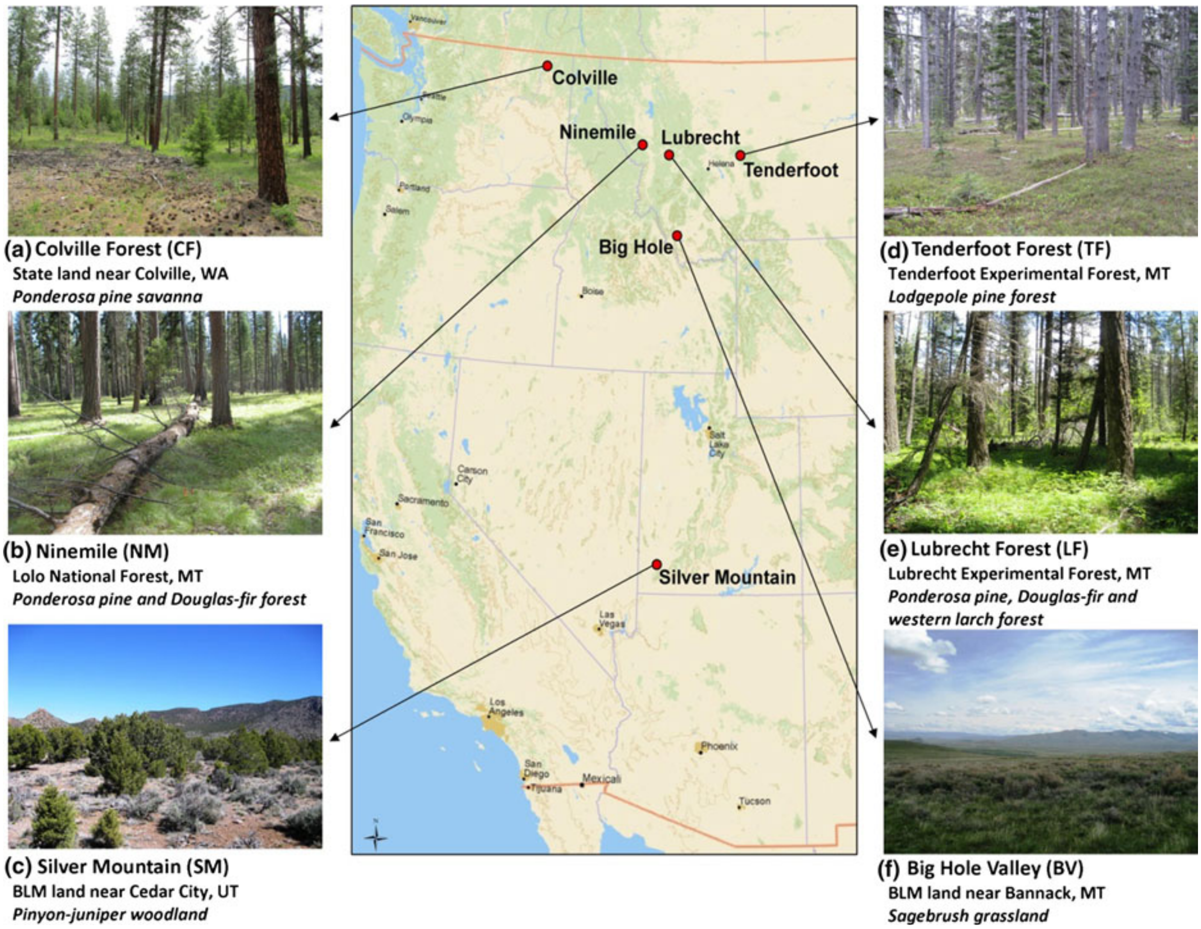

Fig. 2 The six sites selected for this study: **a** Colville Forest (CF) is a pine savanna in eastern Washington, **b** Ninemile Forest (NF) is a ponderosa pine-Douglas-fir grassland that was recently burned by a prescribed fire, **c** Silver Mountain (SM) is a pinyon-juniper woodland in west-central Utah, **d** Tenderfoot Forest (TF) is an even-aged lodgepole pine forest in central Montana, **e** Lubrecht Forest (LF) is a pine-fir-larch forest in west central Montana that was recently thinned as a fuel treatment, **f** Bighole Valley (BV) is a sagebrush grassland in southwest Montana

difficult to measure in the context of this study. We also sampled particle density, mineral content, and bulk density for seven surface components which was used to compute loadings, but those results were reported in Keane et al. (2012, in press). For canopy fuels, we calculated biomass of burnable canopy material (dry weight mass in kg of all fuels less than 3 mm diameter) from allometric tree structural relationships summarized into two measurements—canopy fuel loading (CFL, kg m^{-2}) and canopy bulk density (CBD, kg m^{-3}). *Canopy cover* (CC, percent) is the vertically projected cover of all canopy fuels including the particles greater than 3 mm diameter.

We installed a nested grid design within a square 1.0 km^2 (1,000 m by 1,000 m) grid in the center of each selected study site (Fig. 3) (Bellehumeur and Legendre 1998; McCollum 2005). Corners of this "sampling grid" were monumented and georeferenced, and the sides were oriented along the four cardinal directions. Transects were established across each corner, and at 100 m intervals along each grid side. Starting in the NW corner, we established sampling points at 200 m distances along each of the west-east running transects, but staggered the start of the 200 m distance by 100 m on every other transect (Fig. 3). This design provided additional distances between sampling points.

We established a set of nested plots at each grid sampling point (Fig. 4). The largest plot was a 400 m^2 circular *macroplot* that was established at each sample

Table 2 General description of the selected study sites

Site name	Code	Habitat type[a]	Cover type	Structural stage	Primary fuels	Dominant undergrowth[b]	Past activities
Lubrecht ForesT	LF	PSME/VACA, PSME/VAGL	Ponderosa pine/ Douglas-fir/western larch	Mature	Partially decomposed light thinning slash	Pinegrass, snowberry, spirea, and elk sedge	Recent thinning nine years prior to sampling
Tenderfoot Forest	TF	ABLA/VASC	Lodgepole pine	Pole-mature	Low live shrub, scattered woody	Grouse whortleberry, elk sedge, arnica	Low intensity surface fire approximately 64 years prior to sampling
Ninemile	NM	PSME/PHMA PSME/SYAL	Ponderosa pine-Douglas fir	Mature	Grass, widely scattered thinning slash	Pinegrass, elk sedge, snowberry, kinnikinnick	Thinning and prescribed burn approximately 8 years prior to sampling
Bighole Valley	BV	NA	Sagebrush grasslands	Mature	Sagebrush, grass	Mountain sagebrush, bluebunch wheatgrass,	History of cattle grazing
Silver Mountain	SM	NA	Pinyon Pine/ Juniper	Mature	Patchy, light herbaceous fuels	Sagebrush, ephedra, poa	History of cattle grazing, Wildland fire excluded from these landscapes.
Colville Forest	CF	PSME/SYAL PSME/VACA	Ponderosa pine savanna	Mature	Grass, scattered woody	Rough fescue, pinegrass, snowberry	History of frequent burning and grazing

[a] Habitat types were keyed from Pfister et al. (1977) and the codes are PSME-Douglas-fir (*Pseudotsuga mensezii*), ABLA-subalpine fir (*Abies lasiocarpa)*, PHMA-ninebark (*Physocarpus malvaceus*), VASC-grouse whortleberry (*Vaccinium scoparium*), VAGL-blue huckleberry (*Vaccinium globulare*), VACA-dwarf huckleberry (*Vaccinium caespitosum*), SYAL-snowberry (*Symphoricarpus alba*)

[b] Scientific names are pinegrass (*Calamgrostis rubescens*), rough fescue (*Festuca scabrella*), kinnikinnick (*Arctostaphylos uva-ursi*), elk sedge (Carex geyerii), spirea (*Spirea betulafolia*), mountain sagebrush (*Artemisia tridentata vaseyana*), arnica (*Arnica latifolia*), sagebrush (*Artemisia tridentate)*, poa (*Poa secunda* and *bulbosa*), ephedra (*Ephedra viridis*)

point for measuring tree population data. Measured tree data were used as input to allometric biomass equations to calculate the canopy fuels variables (Reinhardt et al. 2006). We recorded species and health class for all trees above 10 cm DBH (diameter breast height), then measured their DBH (cm), tree height (m), canopy fuel base height (m), crown class, crown position, and live crown ratio using FIREMON methods (Lutes et al. 2006).

We then installed a 100 m^2 circular *subplot* within the macroplot on which we sampled logs (>8 cm diameter) and live trees greater than 1.37 meters tall but less than 10 cm DBH (saplings) (Fig. 4). Saplings were individually measured for species, DBH class (2 cm size classes), height, and crown base height (Lutes et al. 2006). These sapling measurements were augmented with the tree measurements to compute canopy fuel variables. We also measured the length, and the small and large end diameters, of each log (downed dead woody fuel particles greater than 8 cm diameter) within subplot boundaries, and then assessed the log's decay class using the five rot classes described in the FIREMON Fuel Loading method. A log's length was measured along the longitudinal axis and terminated at the end of log or boundary of subplot; only logs whose central longitudinal axis was above the litter-duff surface were measured. From a 10 % random sample of measured logs, we sawed at least three cross-sectional areas from selected logs within the subplot to measure log densities which were used to compute loading. Sub-sampled logs were selected for each species and rot class. Cut log samples were placed in labeled paper bags and transported back to the lab where they were dried and weighed to determine particle density.

We then centered a 1 m^2 square *microplot* over each grid point and measured tree seedling characteristics, loadings of shrub, herb, and fine woody (<8 cm diameter twigs and branches), depth of duff and litter, and cover and height of all vascular plant species (Fig. 4). Seedlings (trees <1.37 meters in height) were

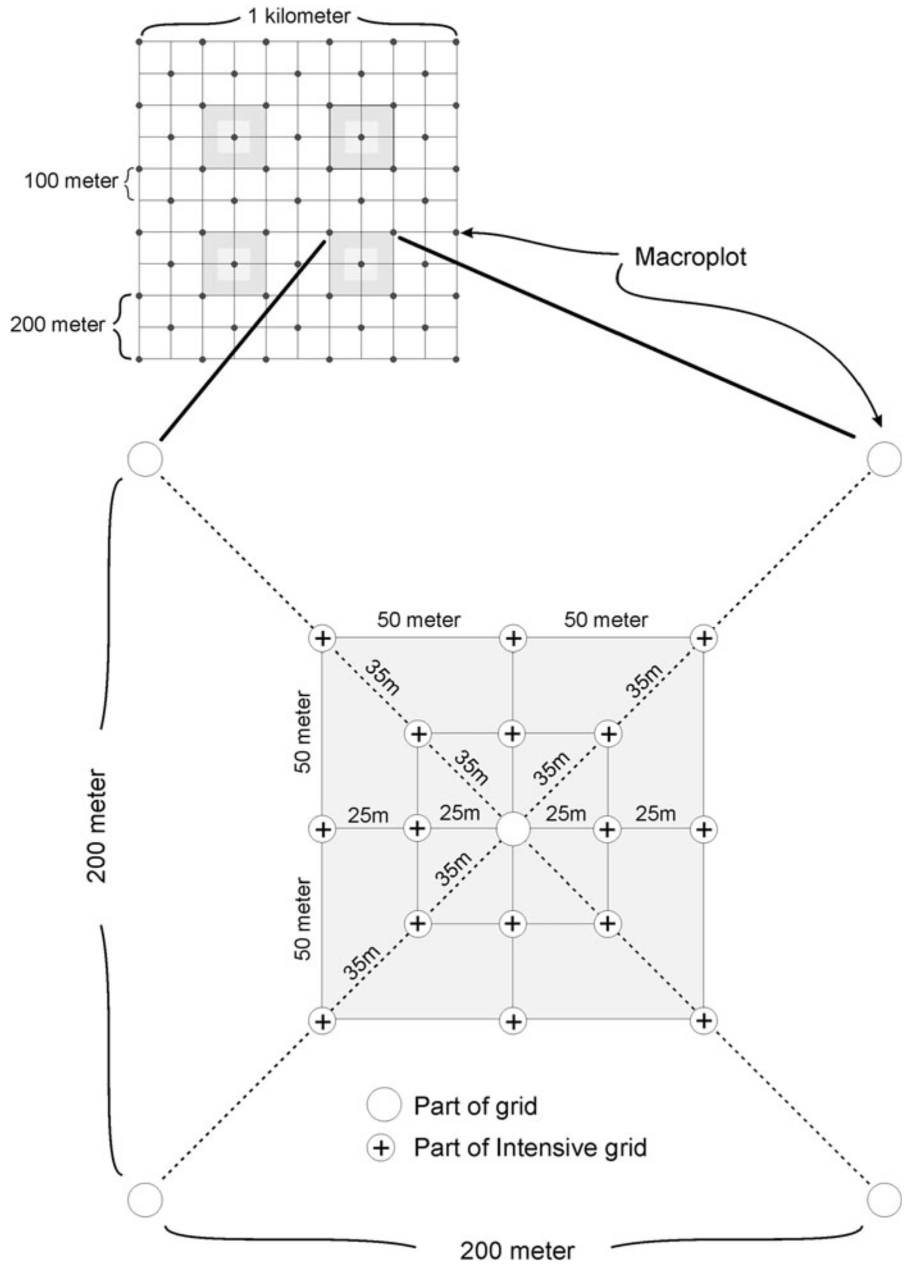

Fig. 3 The sample grid installed in the center of each selected study area with the four sub-grid areas that received additional sampling to intensify the grid. A set of *nested plots* were installed at each of the sample points shown in the grid

counted by species and height classes. Fuel loadings for the 1 h, 10 h, 100 h, shrub, and herb fuel components were visually estimated using the photo-load technique (Keane and Dickinson 2007), and depth of both the duff and litter were measured at 13 points within the microplot (Fig. 4) using FIREMON Fuel Loading methods where we inserted a ruler downward through the duff and litter until we hit mineral soil. Vertically projected canopy cover (%) and average height (m) of all vascular plant species within the microplot were estimated using the Cover Frequency method in FIREMON.

At four sampling points in the grid we installed an intensive macroplot and microplot grid to intensify sampling and to increase the number of fine scale distances (Fig. 3). We installed a 5 m by 5 m grid containing 25 microplots with the center of the microplot grid located at the center of the sampling grid point. All 25 microplots in the intensive microplot grid were measured exactly the same as the other

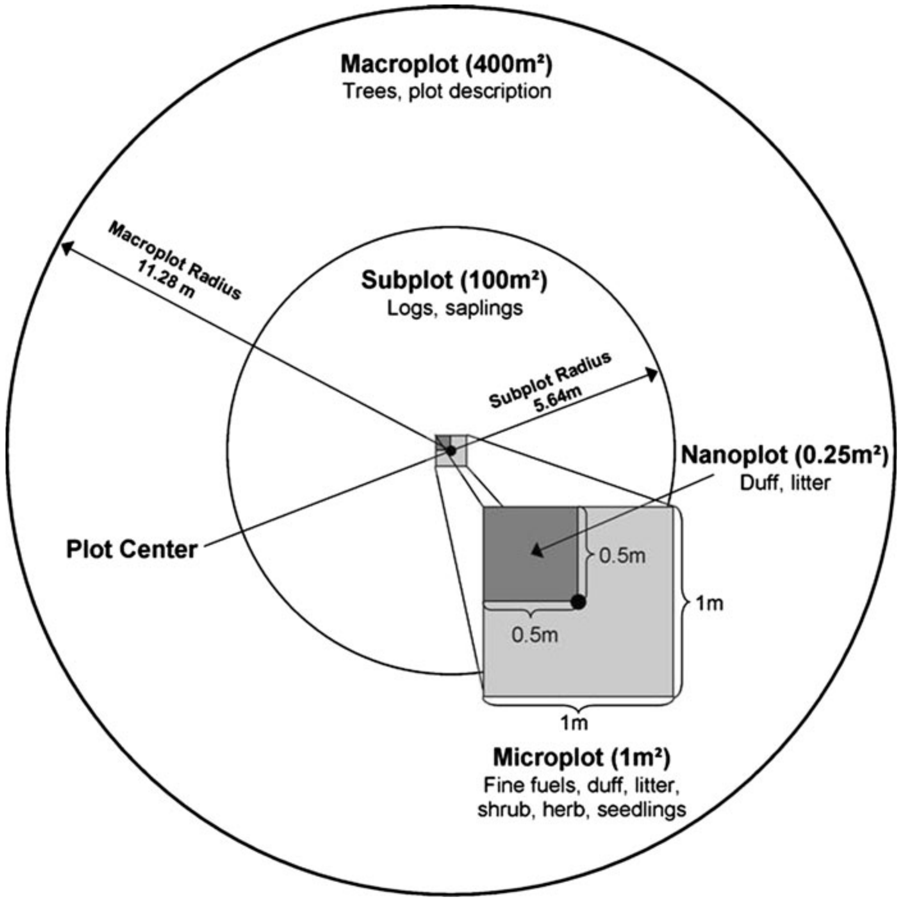

Fig. 4 The set of *nested plots* that was established at each of the sampling points in the grid. All *plots* used the same plot center. The 400 m^2circular macroplot was used to measure trees; the 100 m^2 circular subplot was used to measure logs and saplings; the 1 m^2 square microplot was used to measure fine fuel loading, tree seedling density, and shrub and herb biomass, cover, and height; and the 0.25 m^2 square nanoplot was used to measure duff and litter depths and loading

microplots on the 1 km^2 sampling grid. We also randomly selected 20 % of the microplots, including those on the intensive microplot grid, to destructively sample for all fuel components to measure actual fuel loadings to calibrate the photoload visual estimates. On these randomly selected microplots, we collected all the fuel for the three fine down, dead woody, shrub, and herb components and sorted them on site into separate paper bags. These bags were labeled and placed in a burlap bag for transport to the lab where they were dried and weighed to determine loading.

Last, we installed a 0.25 m^2 (50 × 50 cm) square *nanoplot* in the northwest corner of the microplot to measure duff and litter fuel loadings (Fig. 4). We measured duff and litter depths for five points at each corner of the nanoplot and directly in the middle. Duff and litter depths were measured using FIREMON procedures from the top of the mineral soil to the top of the litter material at the point of measurement. We then collected duff and litter material from nanoplots on the 20 % randomly selected microplots mentioned above using a flat shovel and stored the extracted profile in a labeled burlap or paper bag (Snell 1979; Stephens et al. 2004). Litter and duff were dried and weighed to determine loading then converted to bulk density using the depth measurements, and the calculated bulk densities were used to calculate duff + litter loading for all the remaining microplots from measured depths. Dry weights of all collected fuels were calculated by weighing the fuel after it has been dried in an oven for 3 days at 80 °C.

Analysis

Calculating surface fuel loadings

Fine fuel loadings were estimated for all microplots using the photoload sampling technique because it was easy, fast, and somewhat accurate (Sikkink and Keane 2008). However, photoload loading estimates are based on visual assessments, which may be of sufficient resolution and quality for fire management applications, but probably should be further refined for research purposes. Therefore, we regressed the photoload estimates for the fine woody, shrub, and herb fuels to the destructively sampled loading estimates for the 20 % sub-sampled microplots and used the slope of the regression line as a correction factor to multiply the remaining photoload estimates to "correct" the visual photoload estimates for all microplots. The goodness of fit (R^2) ranged from 0.47 to 0.83 and correction factors ranged from 0.3 to 1.46 for fine fuel loadings (Keane et al. (2012, in press).

Log loadings on the subplot were calculated by summing the mass of all measured logs on the macroplot and dividing by 100 (area of subplot) to convert to kg m^{-2}. Mass of individual logs (kg) was calculated by multiplying log volume by the measured wood density (D, kg m^{-3}). Log volume was calculated using the following formula:

$$V = \frac{l}{3}\left[(a_s + a_l) + \sqrt{(a_s a_l)}\right] \quad (1)$$

where a_s and a_l are the areas (m^2) of the small and large end of the fuel particle ($a = \pi d^2/4$ where d is the log diameter), respectively, and l is the length of the log (m) assuming log shape is approximated as a truncated frustum. Wood density (kg m^{-3}) was directly measured from all cross-sectional samples taken by species and rot class from the site. If a species or rot class density was un-sampled, we used values taken from the literature (Harmon et al. 2008).

Loading (kg m^{-2}) for the duff and litter layer was calculated by multiplying the volume of the duff and litter layer (m^3) by measured bulk density (kg m^3) and dividing by area of the microplot (m^2) (Snell 1979; Woodard and Martin 1980; Stephens et al. 2004). Volume was calculated by multiplying average depth (m) from the 13 measurements by microplot area (1 m^2). Bulk density for duff + litter is taken from the average of all bulk densities calculated from the 20 % destructively collected nanoplot samples (Keane et al. 2012, in press). To compute field sampled duff + litter bulk densities, we first computed loading by dividing dry weight of the litter + duff profile by the nanoplot area (0.25 m^2). We then divided this loading by the volume of the nanoplot duff-litter profile using the average depth of the five nanoplot depth measurements and nanoplot area.

Calculating crown fuel variables

Canopy fuel loading (CFL) and canopy bulk density (CBD) were computed using the FUELCALC program (Reeves et al. 2009), which computes several canopy fuel characteristics based on allometric equations relating individual tree size, canopy, and species characteristics to crown biomass. CFL is computed by dividing the sum of all burnable canopy biomass (particles <3 mm diameter) by the area of the macroplot (400 m^2). FUELCALC then computes vertical canopy fuel distribution using the Reinhardt et al. (2006) algorithms that distribute crown biomass over the live crown for each tree and divides the canopy fuel into horizontal layers of a user-specified width and reports the CBD value for the layer with the greatest bulk density. Canopy cover (CC, percent) was visually estimated in the field at the macroplot level using FIREMON methods.

Scaling spatial variability

We used spatial autocorrelation analysis to fit semivariograms for the spatial distribution of loadings of each surface and canopy fuel component to determine the scale at which that fuel component is best measured and described (SAS/STAT(R) 9.3 Users Guide http://support.sas.com/documentation). Four types of models were used to fit the spatial fuel loading data to the spatial variogram (Gaussian, pure nugget, exponential, and spherical) and the range, sill, and nugget values were taken from model with the best goodness of fit statistics (R^2, standard error, mean square error). Often, we found poor results for two or more variogram models because of abundant zero data values, and in these cases we picked the model that gave us the lowest semivariogram range, or if there were greater than 25 % zero values, we eliminated that fuel component from the spatial analysis. We recorded range, sill, and nugget values by fuel component (particle size) and sample site to evaluate if the spatial properties of fuels are scalable and constant across components and ecosystems. We also evaluated whether spatial variation in the fuel variable is isotropic and whether the variation is stationary—homogeneous in space. Two spatial statistics were also computed to describe the spatial distribution of fuel variables—Moran's I and Geary's C—but results are minimally reported here (see Keane et al. 2012, in press).

We estimated scaling factors for all surface fuel components by performing linear (Y = a + bX) and non-linear (ln(Y) = a + (b)ln(x)) regression, using the semivariogram range as the dependent variable (Y) and surface fuel component particle size as the independent variable (Y). Duff + litter particle size was assumed to be 0.2 cm as derived from needle dimensions measured from the collections taken at the destructively sampled plots (Keane et al. 2012, in press). Herbaceous particle diameter size was assigned a value of 0.1 cm and shrub particle size was assigned 0.5 cm based on measurements taken from the plants cut in the destructively sampled plots and from values in the literature. Because logs were rare across most site grids, loadings for downed woody fuels greater than 8 cm (1,000 h) were stratified into three broad size classes (8–11, 11–16, 16 + cm) to fit the loading distribution of coarse woody debris. The midpoints of these diameter classes (9.5, 13, and 22 cm) were used in the regression analyses. Canopy fuels were not included in the scaling analyses but were correlated to surface fuel loadings.

Results

Spatial variability

Surface fuels

It appeared that most surface fuel components were highly variable both within and across study sites (Fig. 5). The highest loads were found in the duff + litter fuel component ranging from 0.2 (BV) to 11.3 kg m^{-2} (LF), which comprised over 90 % of the total fuel load for the fuelbed (see Table 2 for sample site descriptions and codes). Duff + litter loads also had high standard deviations (0.22–6.6 kg m^{-2}), but some of the lowest coefficients of variation (58–149 %) with respect to the other fuel components (Keane et al. 2012, in press). Logs, the largest down woody fuel component (1,000 h), had the highest variability of all down woody components across all sites (from no logs in the BV sagebrush-grassland to an average of 0.57 kg m^{-2} in TF lodgepole pine forests) with low standard deviations (0.57 kg m^{-2} at TF), yet their coefficients of variations were approximately the same as the other woody fuel components (101 % at NM pine-fir to 603 % at SM pinyon-juniper). One hour fuel loadings were low ranging from 0.005 (BV) to 0.066 kg m^{-2} (TF) with high coefficients of variation (80 % at CF to 187 % at NM). The 10 h woody fuels averages were higher (0.009 for BV to 0.458 for LF) for four sites (LF, TF, BV, and SM), probably as a result of management activities, and as a consequence, the variability was also the highest with ranges (max–min) of 0.214 (BV) to 9.859 kg m^{-2} (LF). The sagebrush grassland BV loadings were low and variable because sagebrush shrubs rarely produced woody material greater than 2.5 cm in diameter. Shrub and herbaceous loads were the least variable of all surface fuels with shrub loading average ranging from 0.05 (sites LF, TF, CF) to 0.225 kg m^{-2} (sagebrush BV) with low standard deviations (0.042 kg m^{-2} in TF lodgepole to 0.187 kg m^{-2} in SM pinyon-juniper). Herb loadings were low for all sites (0.011 kg m^{-2} at SM to 0.056 kg m^{-2} at CF) with correspondingly low standard deviations and ranges (0.019–0.112 kg m^{-2}).

In general, all spatial semivariogram statistics seemed to increase with fuel particle size (Table 3; Fig. 6) with the smallest particle sized fuel components (duff + litter, herbs, 1 h, and shrubs) having the lowest values for sill and nugget. Duff + litter had both the lowest (0.063) and the highest (3.59) values for the sill, indicating a great disparity in spatial variance across sites for this component. Shrub fuels showed similar behavior in that low sill values (<0.7) were calculated for all but the shrubby pinyon-juniper SM site (sill >2.0). In contrast, 1 h and herb fuels had some of the lowest spatial variance with sills ranging from 0.03 to 0.67 in semivariance. Downed woody fuels semivariance seemed positively correlated with the size of the woody particle except for 1,000 h fuels where semivariance generally decreased. Sill values for 1 h fuels (0.03–0.28) were generally lower than 10 h fuels (0.35–2.19), which were generally lower than 100 h fuels (0.76–3.59), but values for the 1,000 h fuels (0.05–2.12) were more similar to 10 h fuels and did not increase over 100 h fuels. This is in contrast to 1,000 h fuels which had the highest standard deviations, but those deviations were less than 50 % of the mean (Fig. 5).

Semivariogram range statistics provided the most important information on the spatial dynamics of surface and canopy fuels because range values represent inherent patch sizes. Overall, it appeared that the range generally increased with fuel particle size (Table 3). Duff + litter ranges were the lowest and

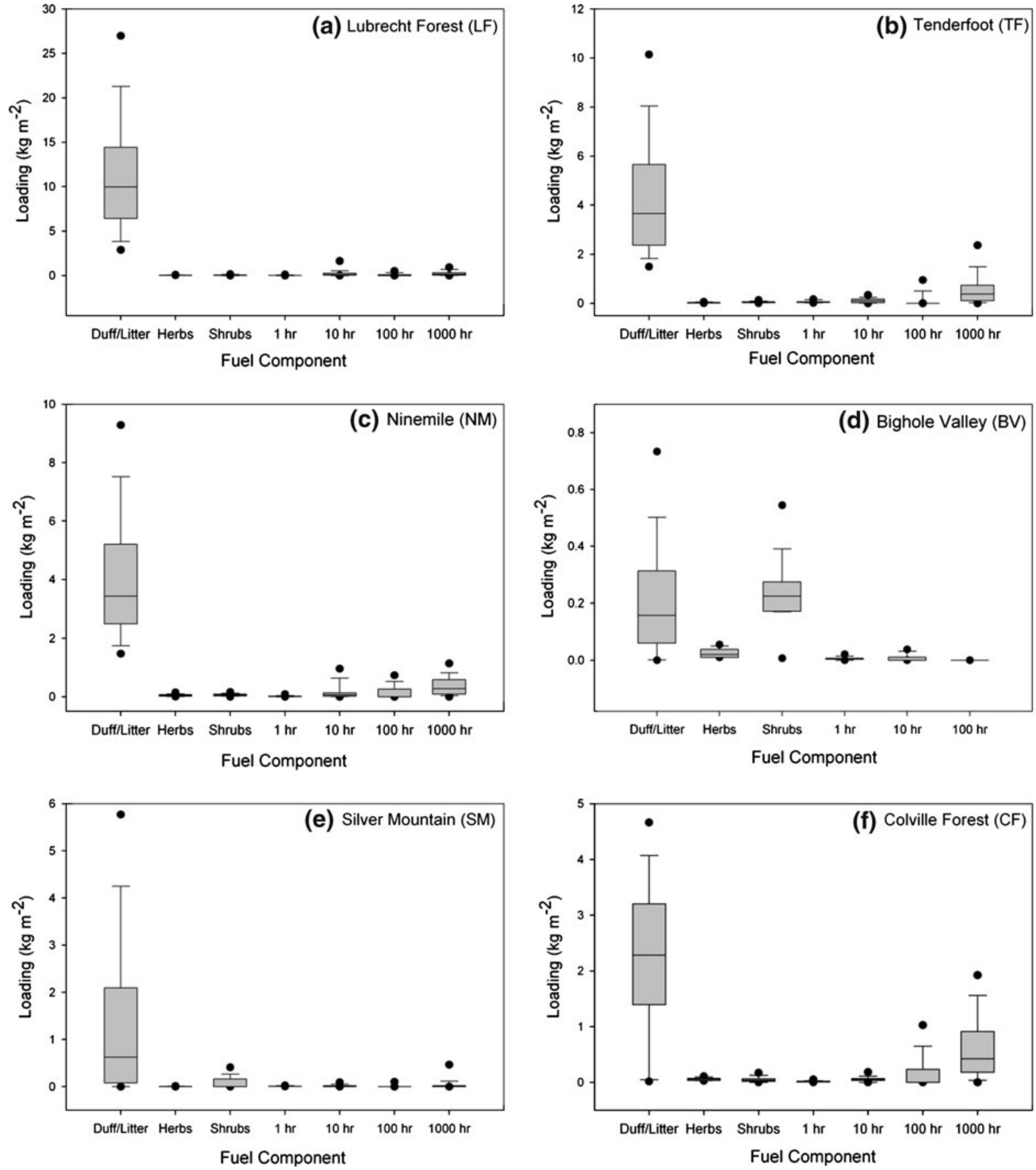

Fig. 5 *Box* and *whisker plots* of measured loadings (kg m^{-2}) for each fuel component across all six sample sites: **a** Lubrecht Forest (LF), **b** Tenderfoot Forest (TF), **c** Ninemile Forest (NF), **d** Bighole Valley (BV), **e** Silver Mountain (SM), and **f** Colville Forest (CF). Note that the scales of the Y-axis are different for each site to show that the loading distribution and variability across components are similar across sites but the magnitudes are different

span from 0.5 at LF pine-fir-larch to 2.5 m at CF pine savanna. Herbs have the next lowest patch size with ranges that went from 0.5 on LF to 3.5 m on NM, both were pine-fir sites. Shrub fuels appeared to vary at the next highest scale with ranges from 0.9 (CF) to 3.6 m (LF) with the highest of 15.1 m at SM indicating higher shrub discontinuity in pinyon-juniper ecosystems. Fine woody fuels varied at about the same scale as shrubs depending on particle size with 1 h fuel ranges from 2.5 (SM) to 16.3 m at LF, 10 h ranges from 0.88 at BV to 11 m at TF, and 100 h ranges from 2.4 to 4.6 m. Logs had the highest inherent patch sizes ranging from 22 at NM to 157 m at SM. Semivariogram ranges for 100 h woody fuels were more consistent than most of the finer fuels which is probably a result of the rarity of 100 h fuel particles on nearly all study sites.

Spatial variogram nugget values generally increased with particle size, but these results were highly site specific (Fig. 6). Overall nugget results were confusing and did not provide any additional information about spatial fuel variability because it was difficult to fit semivariograms with the data collected in this project (Keane et al. 2012, in press). Nugget values usually represent the amount of error involved in the measurement of the response variable, in this case fuel loading. Nugget values were the lowest for these loading measurements of fine woody debris (1, 10, 100 h) probably because they were quantified by corrected visual estimates. The highest nugget values (1.1, 1.7) were for logs, which were easier to measure but were rarer within the sampling grid. Moran I values were low for all fuel components (<0.4), but they were highest for the finer fuel components of duff + litter, shrubs, and 1 h woody fuels indicating that these fuels have the greatest spatial structure.

Canopy fuels

Canopy fuel characteristics were quite similar across all forested sites and across all three variables (Fig. 7). The canopy characteristic used most in fire management, canopy bulk density (CBD), ranged from 0.02 to 0.28 kg m^{-3} with standard deviations from 0.01 to 0.18, but the coefficient of variation only ranged from only 48 to 65 %. The variabilities of CBD, CFL, and CC were comparable across sites, especially when they were standardized with the mean (CVs were around 50 % of mean ranging from 20 to 65 %). Variabilities of canopy variables were high for the SM pinyon-juniper forest because it had a discontinuous forest canopy and highly dense tree crowns. The Bighole Valley (BV) site was a sagebrush-grassland site so there were no canopy fuels on any of the plots within that grid.

Spatial statistics for CC, CBD, and CFL spatial variograms also seemed remarkably similar across sites (Table 3). There were no range and sill values for the CF and NM sites because both variograms could only be fitted with a pure nugget model, and no canopy variogram statistics are reported for the BV grassland site because there were no trees. Values for the semivariogram ranges for the remaining sites ranged from 100 to 440 m for CBD, 310–600 m for CFL, and 230–407 m for CC. The lowest ranges were found for the closed forest of LF and TF (lodgepole), while the highest values were for the open SM and NM forests. CFL had the highest patch sizes (310–600 m) and these were significantly different from CBD and CC ($p < 0.05$). The sill and nugget were significantly different across all three canopy characteristics with CBD consistently having the lower semi-variance and CC with the highest (Table 3), probably due to differences in how each are estimated. Moran's I statistics were also quite low for the canopy fuel characteristics with the highest value at 0.17 in the TF lodgepole pine site indicating a lack of spatial structure in canopy characteristics (Keane et al. 2012, in press). Moran's I, however, was statistically similar across the three canopy characteristics with CC having the greatest variation in spatial structure.

Scaling

Regressions of the range to fuel particle size across all sites and for each site provided a means to quantify scaling factors for surface fuels. Using linear regression, we found that there was approximately a 4.67 m increase (slope) in the semivariogram range for each cm increase in fuel particle diameter size when the range data was pooled across all sites (Slope b value with a significant R^2 of 0.66 but a high standard error of 21 m) and when we transformed the data using the natural log (non-linear regression), we got similar results but with lower standard error (significant R^2 of 0.65 and standard error of 2.7 m) (Table 4; Fig. 8). We also found that the linear regression scaling factors (Slope-b) were greatly different across sites ranging from 2.46 for pine-fir NM site to 9.97 m for the lodgepole TF site (Table 4), but the goodness of fit (all R^2 significant ranging from 0.71 to 0.91) and standard errors (1.6–24 m) were somewhat similar, except at the SM site where the intercept (4.65 m), slope (-0.46), and R^2 (0.02) indicated an extremely poor

Table 3 Semi-variogram statistics for all surface and canopy fuel components across the six sites

Fuel component	Big Hole (BV) sagebrush grassland[a]	Silver Mountain (SM) pinyon juniper	Colville Forest (CF) pine savannah	Ninemile (NM) pine-fir	Lubrecht Forest (LF) pine-fir-larch	Tenderfoot Forest (TF) lodgepole pine
Range (m)						
1 h	4.67	2.50	2.83	16.30	8.90	6.02
10 h	6.60	2.46	0.88	4.95	2.23	11.10
100 h	No 100 h	2.46	2.54	4.56	2.41	4.14
1,000 h	No Logs	No Logs	84.01	22.01	87.30	157.01
Shrub	2.44	15.10	0.85	1.79	3.61	2.66
Herb	0.72	1.11	0.80	3.50	0.52	1.83
Duff/litter	0.45	1.41	2.54	1.29	0.48	0.85
CFL (kg m^{-2})	–	560.00	–	600.00	310.00	560.00
CBD (kg m^{-3})	–	440.00	–	412.00	100.00	120.00
CC (%)	–	407.00	–	–	230.00	300.00
Sill ((kg $m^{-2})^2$)						
1 h	0.128	0.174	0.282	0.051	0.029	0.524
10 h	0.350	0.917	0.744	2.188	1.825	1.274
100 h	No 100 h	0.736	3.590	3.510	2.689	1.018
1,000 h	No Logs	2.129	1.967	0.055	1.825	1.778
Shrub	0.657	2.040	0.302	0.634	0.390	0.426
Herb	0.175	0.480	0.140	0.671	0.080	0.200
Duff/litter	0.058	2.770	3.590	0.268	0.445	0.249
CFL (kg m^{-2})	–	0.050	–	0.020	0.017	0.010
CBD (kg m^{-3})	–	0.008	–	0.001	0.001	0.002
CC (%)	–	0.159	–	–	0.048	0.030
Nugget ((kg $m^{-2})^2$)						
1 h	0.072	0.019	0.052	0.007	0.008	0.085
10 h	0.121	0.000	0.000	1.500	0.575	0.478
100 h	No 100 h	0.053	2.260	1.430	0.449	0.190
1,000 h	No Logs	1.142	0.377	0.000	1.700	0.000
Shrub	0.389	0.000	0.000	0.000	0.050	0.000
Herb	0.000	0.000	0.000	0.103	0.000	0.073
Duff/litter	0.059	0.000	2.260	0.115	0.000	0.016
CFL (kg m^{-2})	–	0.050	0.006	0.026	0.015	0.006
CBD (kg m^{-3})	–	0.013	0.001	0.001	0.001	0.001
CC (%)	–	0.202	0.107	0.120	0.103	0.027

Details of variogram models and model fitting are described in Keane et al. (2012, in press). No canopy fuel values are reported for the BV sagebrush grassland because there was no tree canopy. Range and sill values for the CF and NM sites are missing because the low number of data points could only be fit by a pure nugget model which has no range or sill

scaling relationship. Also, non-linear regression results for each site did not improve upon the linear model coefficient of determinations (R^2 ranging from 0.62 to 0.76) but they did improve the standard errors (2–5 m), except for the SM site (Table 4).

Interestingly, the semivariogram ranges were not related to any of the three canopy fuel characteristics (Fig. 9). Canopy loading (CFL) seemed to have the highest correlations with fuel component ranges (<0.40, see Keane et al. 2012, in press), especially for logs and herbs. Canopy cover (CC) had no predictive value for quantifying fuel component patch sizes. Duff + litter semivariogram ranges had the weakest relationships to the three canopy variables

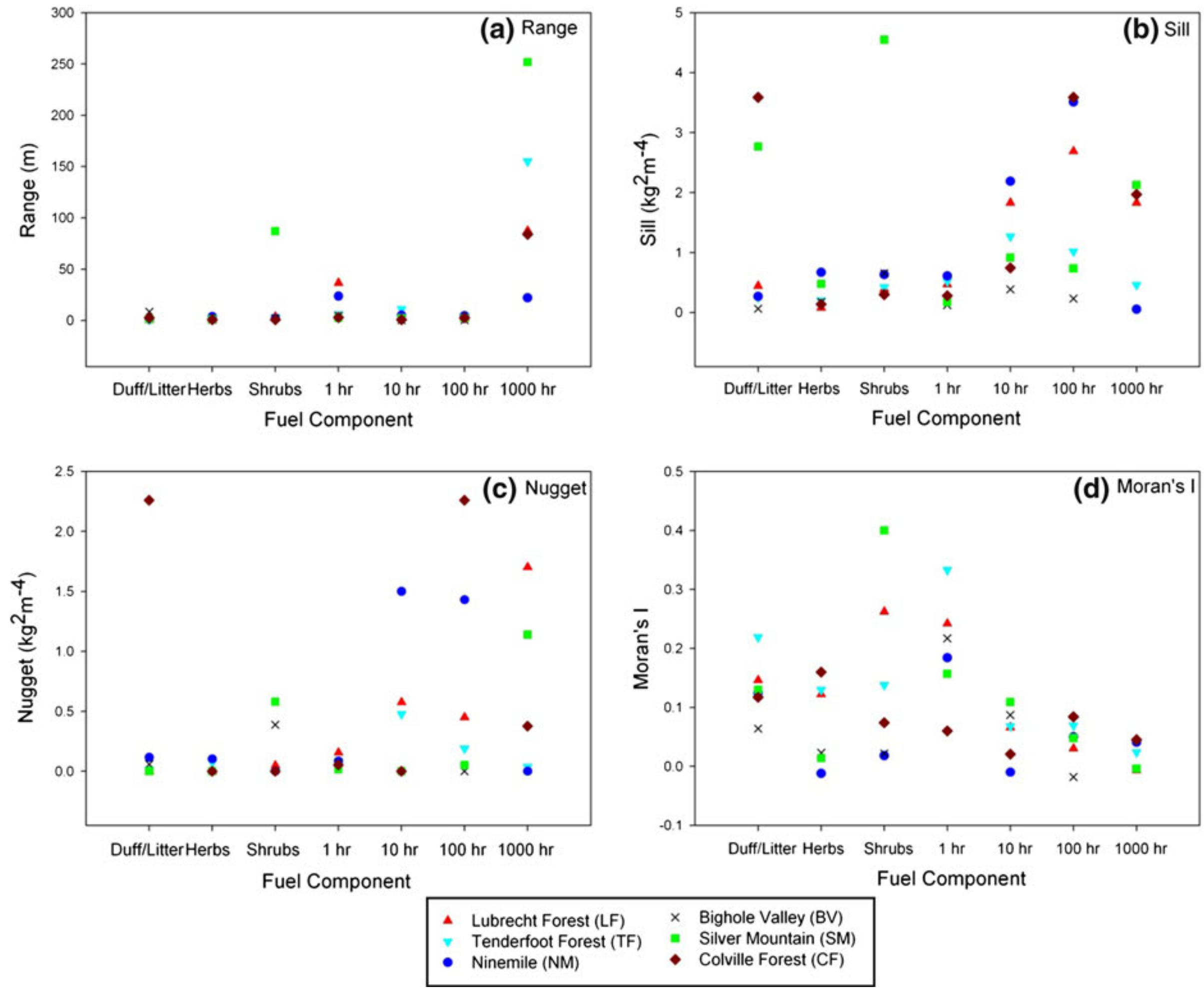

Fig. 6 Spatial semi-variogram statistics for each surface fuel component arranged from smallest to largest particle size across all sample sites: **a** range, **b** sill, **c** nugget, **d** Moran's I

even though canopy loading and bulk densities have been correlated to duff + litter amounts (Keane 2008a).

Discussion

Results from this study showed that surface fuel components varied at different scales; patch sizes tended to increase with increasing fuel particle diameters at a rate of 4.6 m per cm particle diameter (Table 4). However, we also found that there were strong site-to-site differences in this estimate (2–10 m) so the rate of this increase depends on local conditions, such as stand density, species composition, productivity, and stand history (Fig. 8; Table 4). There was also an associated increase in spatial variability as fuel particle and patch sizes increased, both in measurement error (nugget) and overall variation (sill) (Table 3). While this spatial variability and range were poorly explained by canopy fuel variables (Fig. 9) and forest stand characteristics (Keane et al. 2012, in press), they provide important ecological information for the design of fuel measurement, description, and mapping projects; ignoring this variability may have undesirable consequences for fire management.

High spatial variability in wildland fuel is a result of many factors, mainly deposition, decomposition, and disturbance, acting across different time and space

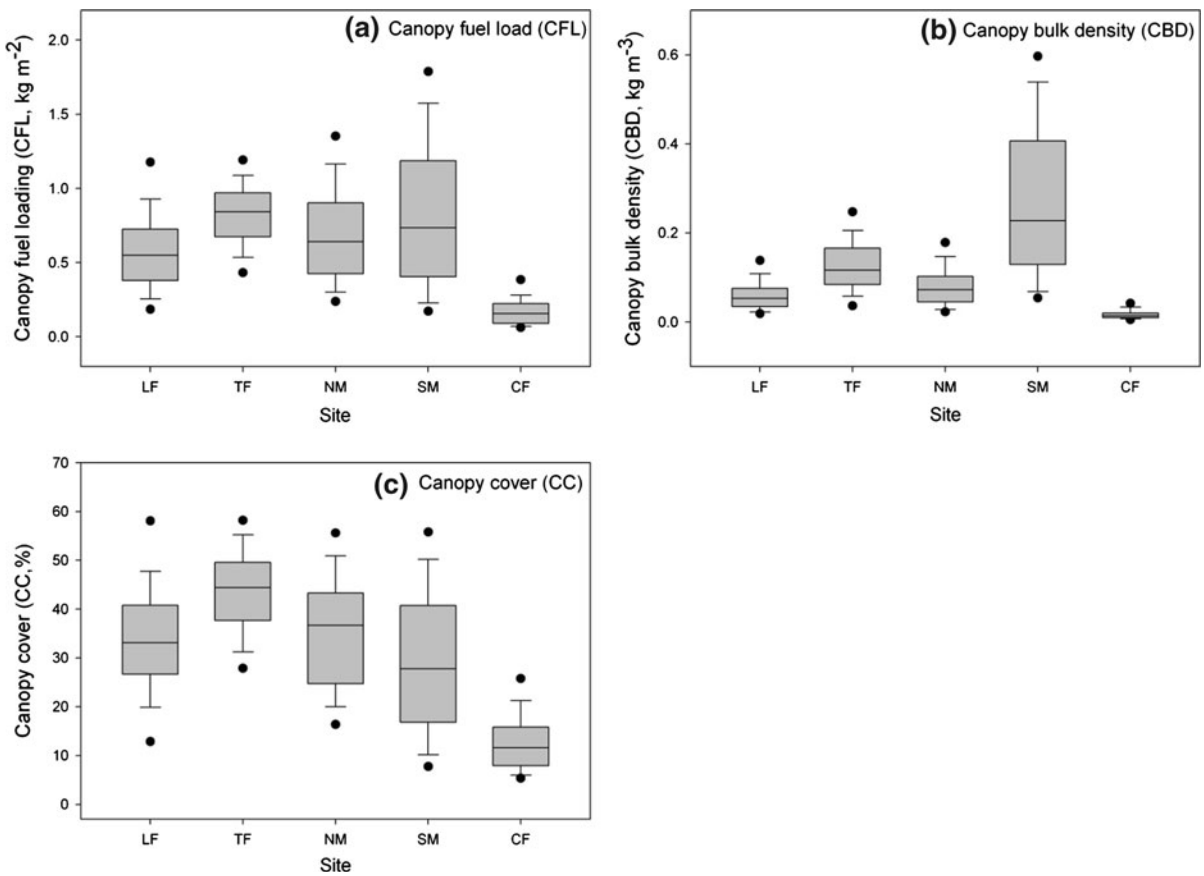

Fig. 7 *Box* and *whisker plots* of the three canopy fuel characteristics. **a** Canopy fuel loading (CFL, kg m^{-2}); **b** canopy bulk density (CBD, kg m^{-3}); and **c** canopy cover (CC, %) across all sites: Lubrecht Forest (LF), Tenderfoot Forest (TF), Ninemile (NM), Silver Mountain (SM), and Colville Forest (CF). Bighole Valley (BV) was a sagebrush grassland site with no trees and therefore the site had no canopy fuels

scales. Most important are the sources of fuel (namely plants) that are distributed across space in complex patterns (Dale 1999). Large fuels, such as branches and boles, tend to accumulate directly under the plant sources, especially trees, and decompose slowly so they are present for longer times. On the other hand, small fuels, such as needles and twigs, can be blown farther away from the parent plant and fall in a more uniform pattern, and they also decompose quicker, which might also explain their low fine scale variability (Harmon et al. 1986; Keane 2008b). Disturbances, such as windthrow, low intensity fires, and insect outbreaks, also impact fuel distributions at finer scales (Van Wagtendonk 1972; Brown and Bevins 1986) because their effects are different across fuel sizes (Brown et al. 1991; Thaxton and Platt 2006). In mixed species stands, for example, fuels can accumulate unevenly beneath trees harvested for canopy fuel reduction (sites LF, CF) or killed by mountain pine beetle (Page and Jenkins 2007; Jenkins et al. 2008), and fires can differentially kill plants and consume fuels in a patchwork of burned, partially burned, and unburned areas that influence future ecosystem responses such as the colonization of future plants (site NM).

Spatial scaling analysis results for the Silver Mountain site were considerably different from all other sites in this study (Tables 3, 4). The low goodness of fit statistics ($R^2 < 0.2$) and negative slope (-0.46) indicated that wildland fuels on this site are distributed at approximately the same scale regardless of size (around 1–15 m). Moreover, nearly all fuel components had high variation (Table 3). This was probably a result of low fuel loadings for all fuel components (<0.2 kg m^{-2}) in this sparse depauperate pinyon-juniper stand. There were many microplots and nanoplots without fine fuels resulting in an

Table 4 Regression statistics for the relationships of semivariogram range to fuel particle size for all and each site

Sites	Intercept—a (SE)	Slope—b (SE)	Coefficient of determination R^2 (%)	Model significance (*p* value)	Residual standard error (m)
Linear model Y = a + bX					
All sites	−0.08 (3.76)	4.62 (0.50)	66.2	<0.0001	21.29
Big Hole Valley	0.74 (1.11)	4.62 (1.71)	70.8	0.074	1.64
Silver Mountain	4.65 (3.13)	−0.46 (1.88)	1.5	0.818	5.98
Colville Forest	−0.54 (7.23)	3.90 (0.78)	78.1	0.002	17.12
Ninemile	4.31 (3.10)	2.46 (0.33)	88.5	<0.0005	7.35
Lubrecht Forest	−8.35 (10.5)	6.07 (1.13)	80.5	0.001	24.77
Tenderfoot Forest	−5.68 (7.62)	9.97 (1.27)	91.2	<0.0005	17.11
Non-linear model (ln(Y) = a + b ln(X))					
All sites	1.58 (0.14)	0.73 (0.08)	64.7	<0.0005	0.97
Big Hole Valley	1.72 (0.57)	0.98 (0.41)	66.1	0.094	0.78
Silver Mountain	1.12 (0.46)	0.21 (0.33)	8.7	0.569	0.98
Colville Forest	1.26 (0.37)	0.80 (0.20)	70.6	0.005	1.10
Ninemile	1.91 (0.32)	0.56 (0.17)	61.7	0.012	0.93
Lubrecht Forest	1.36 (0.38)	0.83 (0.20)	71.3	0.004	1.11
Tenderfoot Forest	1.96 (0.34)	0.85 (0.20)	75.7	0.005	0.95

Loadings for downed woody fuels greater than 8 cm (1,000 h) were stratified into three size classes (8–11 cm, 11–16 cm, 16 + cm) and the midpoints of these diameter classes were used in the regression. All sites described in Table 1

SE standard error

abundance of zero loading values making it difficult to fit a semivariogram model. We probably should have used a larger sampling frame for quantifying fine fuel loadings at this site to minimize zero values and optimize spatial sampling intensities (see next section).

Another interesting finding of this study was the lack of correlation of stand-level variables to fuel component semivariogram ranges (i.e., patch sizes). Few surface fuel range values correlated to canopy fuel characteristics (Fig. 9), and surface fuel component loadings were poorly related to the stand variables of average diameter, average tree height, basal area, and tree density (Keane et al. 2012, in press). Canopy fuel variables were also uncorrelated to surface fuel loadings and their spatial statistics (Fig. 9). These results have been found by others when analyses were done across large regions (Brown and Bevins 1986), but studies where measurements were done at small scales are lacking.

Study limitations

There are some limitations in this study design that may have influenced our quantifications of spatial variability. First, we sampled woody fuels in the uneven size classes commonly used by fire behavior modeling (Table 1), and the stratification of woody fuel loadings by these unbalanced diameter classes may have introduced some unwanted uncertainty. Loadings, especially for 100 h fuels, for example, can be highly variable because particle diameters range from 2.5 to 8 cm resulting in a possible tenfold range in volume or loading. To further compound this problem, branch diameter size distributions differ by species and position in the canopy (Brown 1978). Subalpine fir, for example, has smaller branches than ponderosa pine (Minore 1979; Reinhardt et al. 2006), and as a result, fir branches are never large enough to represent the full 2.5–8 cm diameter range encompassed by 100 h fuel (Table 1). Smoke emissions predictions, carbon inventories, and fuel consumption would be greatly improved if woody fuel particles were sampled at size classes that match the resolution of measurement accuracy, rather than the resolution of the fire models.

Another limitation is that our sampling density and resolution may not have matched the exact scale of the fuel particle spatial distribution (e.g., Silver Mountain). Since we had no prior knowledge of the inherent scale of fuel component loadings, we implemented a

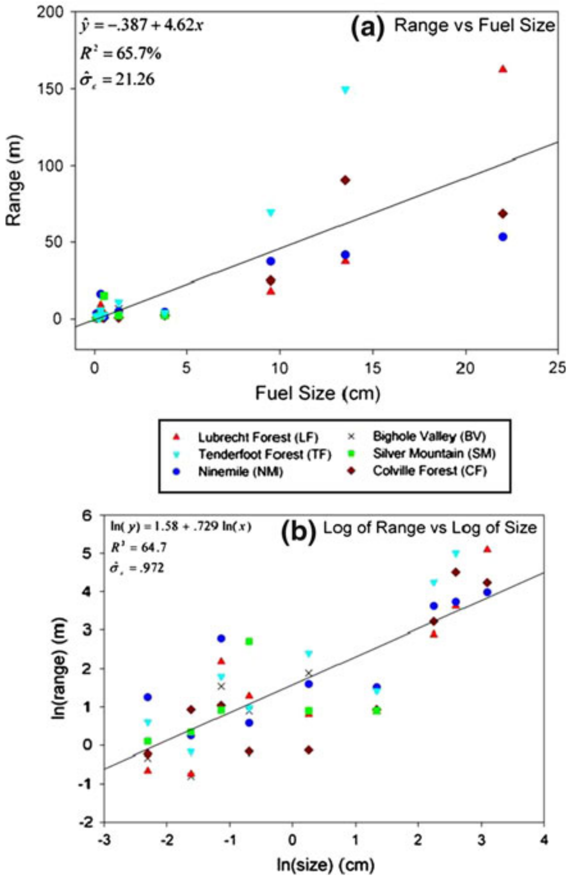

Fig. 8 Regression results for the relationship of the semivariogram range to fuel particle size for all fuel sizes using **a** linear regression and **b** non-linear regression. Loadings for downed woody fuels greater than 8 cm diameter (1,000 h) were stratified into three size classes (8–11, 11–16, 16 + cm) and the midpoints (9.5, 13, and 22 cm) of these diameter classes were used in the regression

methodology that we thought was appropriate. And, because it took over 4 weeks to sample a site, we used only four intensive microplot grids (4 × 25 m^2 = 100 m^2) in the 1 km^2 sample grid. This 1 % sample may be too small for accurate descriptions of spatial variability of surface fuels at fine scales. Moreover, the distance between the subplots used for sampling log loadings may have been too great to accurately describe log spatial variability. Additional analysis of our data revealed that the subplot size was indeed large enough to minimize log fuel sampling variability, but that there should have been more intensive sampling at 5, 10, and 15 m distances. For logistical reasons, we used only four static nested sampling frames for describing fuels, when in reality, some surface fuel components are ineffectively sampled at these scales, as we found from our study results (Table 3). Large branches (100 h) on the SM site, for example, were probably inappropriately sampled with only a 1 m^2 microplot because of abundant zero values (Table 3).

Because of the highly restricted site selection criteria, this study was implemented on only six study sites which represent a small number of forest and range vegetation types in the northern Rocky Mountains. As a result, study results are probably specific to the few sites that we sampled and probably shouldn't be extrapolated to other sites. As mentioned, it took well over a month to conduct the measurements on one study site so our sampling time was somewhat limited because of cost concerns. Moreover, it was difficult to find study sites that fit our selection criteria because the complex interactions between wildland fire, management activities, and topography rarely created the large, flat, homogeneous sites needed for this study. In the future, we will relax site selection criteria and move from small heterogeneous 1 km^2 patches to large landscapes (>1,000 ha).

Management implications

Findings from this study have profound implications in wildland fire science research and management that could fundamentally change the way we measure, classify, and map fuels and model fire in the future. Most importantly, it is clear that each wildland fuel component varied at unique scales and this means that methods for describing and quantifying fuel properties (fuel sampling) must accommodate the inherent scales of each fuel component in their design. Fine fuels, for example, should be sampled with a sampling frame that is large enough to minimize spatial sampling bias but small enough to adequately capture spatial variation (1–5 m). A hierarchically nested fixed-area plot design, similar to the one used in this study, may be a possible solution where fine fuels are sampled within 1–5 m^2 microplots, logs are sampled on 50–100 m^2 plots, and canopy fuels are sampled on 400–1,000 m^2 plots. In addition, it appeared that loadings of surface and canopy fuel components were uncorrelated so any sampling or analysis method that attempts to quantify fuel variability and distribution from stand conditions are suspect. Critical research is needed to develop methods that accurately quantify fuels within fixed

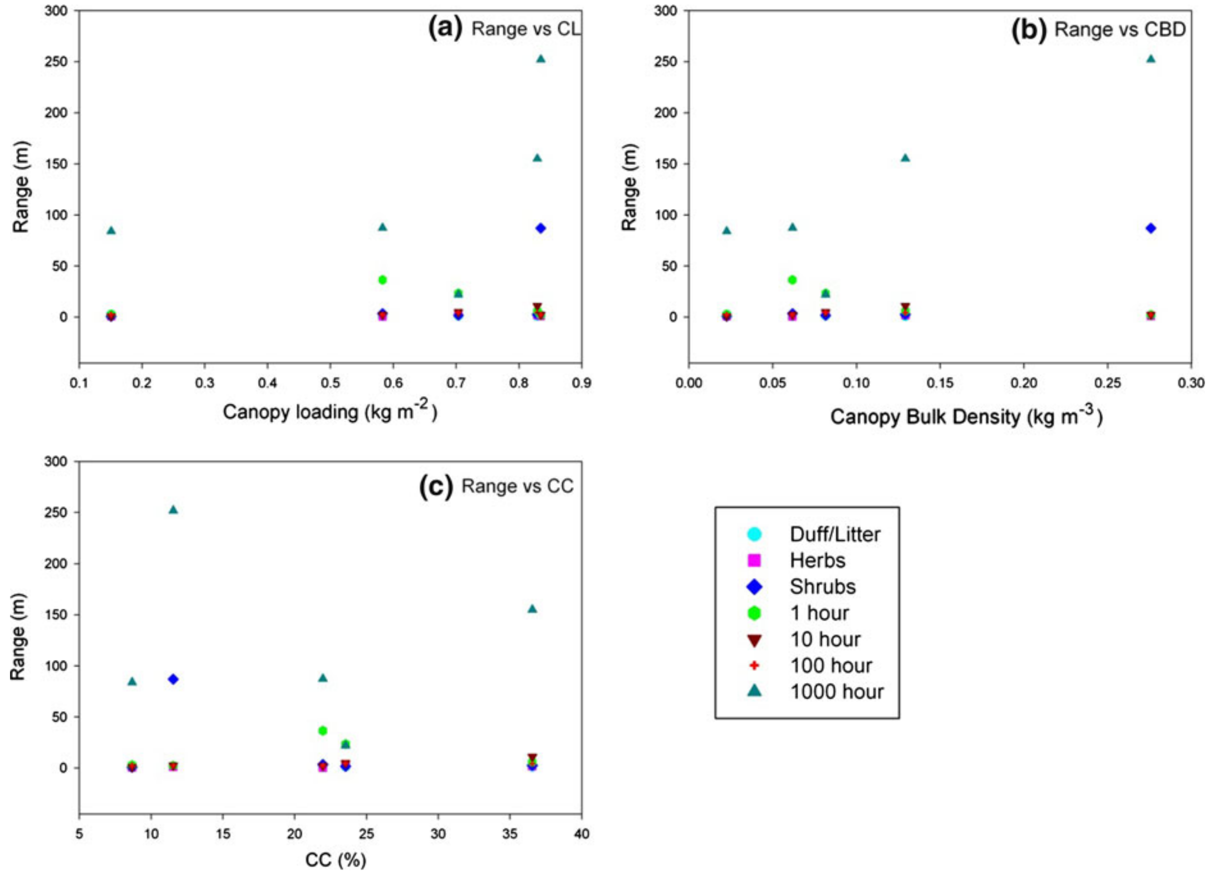

Fig. 9 Relationship of the semi-variogram range for each surface fuel components across all five forested sites to the average of canopy fuel variables of **a** loading (CFL), **b** bulk density (CBD), and **c** cover (CC) across all sites

plots and are also easy to use with limited training and resources.

Wildland fuel mapping must also account for variability of fuels across space. Fine fuel variability within the 30 m pixel size commonly used in many land management mapping efforts may be so high that it may overwhelm fuel quantification, compromise accuracy assessments, and ineffectively predict fire behavior and effects (i.e., fine scale variations in fuel loadings and structure affect fire spread and subsequent fire intensity, see Parsons et al. 2010). The resolution of remotely sensed imagery, biophysical modeling, and GIS analysis probably should match the spatial variation (i.e., patch size) of the fuel component being mapped; twigs, for example, should be mapped using 1–5 m pixel size. Spatially explicit fire behavior and effects models that use fuel maps could intensify the native mapping grid with simulation algorithms that stochastically distribute fuels across space at the appropriate resolutions.

Fuel classifications, such as fire behavior fuel models (Scott and Burgan 2005), fuel loading models (Lutes et al. 2009), and fuel characteristics classification system fuelbeds (Ottmar et al. 2007), may also have limitations for fire behavior and effects applications. These classifications are "point" estimations of fuel loadings, yet many assign the categories from these classifications to large areas using vegetation attributes (Reeves et al. 2009) ignoring the influence of the fuel variability on fire prediction and the lack of correlation of fuel loadings with vegetation attributes (Fig. 9; Keane et al. 2012, in press). The next generation of fuel models may need to contain spatial statistic parameters that can be used to generate realistic spatial distributions of fuel component loadings so that effective fuel maps can be created at any scale and resolution.

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