CSIRO PUBLISHING

International Journal of Wildland Fire **2016**, *25*, 1156–1168
http://dx.doi.org/10.1071/WF16072

Spatial variability of surface fuels in treated and untreated ponderosa pine forests of the southern Rocky Mountains

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Abstract. There is growing consensus that spatial variability in fuel loading at scales down to 0.5 m may govern fire behaviour and effects. However, there remains a lack of understanding of how fuels vary through space in wildland settings. This study quantifies surface fuel loading and its spatial variability in ponderosa pine sites before and after fuels treatment in the southern Rocky Mountains, USA. We found that spatial semivariance for 1- and 100-h fuels, litter and duff following thin-and-burn treatments differed from untreated sites, and was lower than thin-only sites for all fuel components except 1000-h fuels. Fuel component semivariance increased with mean fuel component loading. The scale of spatial autocorrelation for all fuel components and sites ranged from <1 to 48 m, with the shortest distances occurring for the finest fuel components (i.e. duff, litter). Component mean fuel particle diameter strongly predicted ($R^2 = 0.88$) the distance needed to achieve sample independence. Additional work should test if these scaling relationships hold true across forested ecosystems, and could reveal fundamental processes controlling surface fuel variability. Incorporating knowledge of spatial variability into fuel sampling protocols will enhance assessment of wildlife habitat, and fire behaviour and effects modelling, over singular stand-level means.

Additional keywords: Colorado, forest heterogeneity, New Mexico, *Pinus ponderosa*, spatial scaling.

Received 2 August 2015, accepted 18 August 2016, published online 3 October 2016

Introduction

Wildland fuels are commonly assessed by spatially averaging fuel parameters to develop simplified fuel descriptions (Keane 2013). Such approaches have been utilised to quantify the mean fuel load across a range of ecosystems and to assess the effects of forest disturbances and silvicultural techniques on fuel loadings (e.g. Brown and Bevins 1986; Hoffman *et al.* 2007; Page and Jenkins 2007; Strom and Fulé 2007; Woodall and Nagel 2007; Stephens *et al.* 2009). Such simplifications are often necessary to utilise fire behaviour and effects models in land-management planning, but they ignore the inherent spatial complexity of wildland fuels and assume that loading distributions occurring across an area can be captured by spatial averages. However, fuel variability through space may be critical to fully understanding the behaviour and impacts of various ecosystem processes including fire behaviour and effects, population dynamics and community structure (e.g. Thaxton and Platt 2006; Bennett *et al.* 2009; Hiers *et al.* 2009; O'Brien *et al.* 2016).

Findings from fire behaviour and effects research studies have suggested that there are both direct and indirect relationships between wildland fuel variability and subsequent fire behaviour and effects (Keane *et al.* 2012*a*). For example, subtle changes in wildland fuel variability can determine spatial variations in wildland fire spread (Cheney and Gould 1995; Fernandes *et al.* 2004; Hoffman *et al.* 2012, 2015). Although it has been suggested that fine-scale variability in fire spread is transient in nature and can be averaged out over longer time scales for fire planning purposes (Cheney *et al.* 1993; Cruz and Alexander 2013), understanding the mechanisms driving rapid temporal variations in fire spread may have important implications for firefighter safety and tactics. In addition, fine-scale variations in wildland fuels can alter the spatial pattern and variability of fireline intensity, fire residence time and fire residue production (Thaxton and Platt 2006; Hiers *et al.* 2009; Brewer *et al.* 2013). In frequent-fire systems, it has been hypothesised that fine-scale variability in these parameters drives heterogeneity of post-fire species diversity, forest structure and soil carbon accumulation (Hobbs and Atkins 1988; Gibson *et al.* 1990; Thaxton and Platt 2006; Tinkham *et al.* 2016*a*). Advancing our understanding of wildland fuel variability could reveal linkages between fuel

heterogeneity and fire behaviour that could help inform fuel treatment design, optimal fuel sampling designs and fuel mapping efforts (Keane 2015).

Previous research has suggested that wildland fuel loads are highly variable and spatially autocorrelated at fine spatial scales (Kalabokidis and Omi 1992; Reich *et al.* 2004; Hiers *et al.* 2009; Keane *et al.* 2012*b*). This spatial scale of autocorrelation differs by fuel component (e.g. dead down woody fuels, litter, shrubs) and fuel particle diameter or time-lag size classes (e.g. 1-, 10-, 100- and 1000-h down dead woody fuels; Keane *et al.* 2012*b*; Kreye *et al.* 2014). Keane *et al.* (2012*b*) found that semivariogram-modelled ranges scaled as a function of fuel particle diameter, suggesting that general scaling relationships may be developed that relate the size of fuel particles or fuel loading to the pattern and variability of fuel at larger scales. However, Keane *et al.* (2012*b*) discovered that scaling relationships were highly variable from site to site, leading the authors to suggest that site-level factors including stand density, species composition and site level productivity are important drivers of fuel variability. Other studies have also noted that site level factors such as topography, vegetation type, stand history and disturbances may also impact the spatial variability of wildland fuels (Brown and Bevins 1986; Kalabokidis and Omi 1992). Unfortunately, the spatial nature of fuel variability has been assessed for a limited range of ecosystems, representing only a few forest and rangeland vegetation types across the western US (Keane *et al.* 2012*b*). For example, only three sites have been assessed across the western US in ponderosa pine (*Pinus ponderosa* Dougl. ex Laws.) forests, despite the potential importance of fuel heterogeneity in these systems (Keane *et al.* 2012*b*). More research is needed to fully characterise the spatial variability of fuel load across a broad range of ponderosa pine forest conditions to consider the implications of forest management actions and to reveal any underlying mechanisms controlling the scale of fuel variability.

In this study, we focus our efforts on quantifying fuel load variability and spatial scale of autocorrelation within ponderosa pine sites of the southern Rocky Mountains. The objectives of this effort were 3-fold: (1) to quantify the variability and spatial scale of autocorrelation by surface fuel components in untreated, mechanically thinned, and mechanically thinned and burned ponderosa pine forests of the southern Rocky Mountains; (2) to evaluate the effects of fuel treatments on the spatial variability of surface fuel load; and (3) to assess relationships between fuel load variability and spatial scale of autocorrelation with fuel particle size and total fuel loading. We utilised semivariograms to estimate the variability and spatial autocorrelation of measured sample points for each fuel component and compared the estimated variance and spatial autocorrelation scale across the treatments. Furthermore, we utilised power-law functions to investigate the relationship between fuel variability and total fuel load and between fuel particle size and spatial scale of autocorrelation.

Methods

Study location

We selected six sampling locations across the southern Rocky Mountains that represent a wide range of ponderosa pine-dominated forests and current fuel treatment prescriptions within the region (Fig. 1). Ponderosa pine-dominated forests are widespread across the southern Rocky Mountains, occupying the lower treeline ecotone between grassland or shrub steppe and the more productive montane dry mixed conifer forest systems (Fig. 1; Comer *et al.* 2002). Productivity and complexity in species composition within ponderosa pine forests increase with elevation and moisture. At lower xeric sites, other species often include gambel oak (*Quercus gambelii* Nutt.) and Rocky Mountain juniper (*Juniperus scopulorum* Sarg.), whereas at higher, more mesic sites, other species including quaking aspen (*Populus tremuloides* Michx.), Douglas-fir (*Pseudotsuga menziesii* var. *glauca* Franco) and blue spruce (*Picea pungens* Engelm.) are frequently encountered (Peet 1981).

Potential sampling locations were identified in consultation with regional and local USDA Forest Service personnel to represent the range of ponderosa pine forests and current fuel treatment prescriptions across the region (Fig. 1). Potential sampling locations were restricted to areas that had experienced fire exclusion over the last 80 years and contained both untreated and recently treated (either mechanically thinned or mechanically thinned and burned within the past 8 years) stands that: (1) were within 10 km of each other; (2) were each large enough to accommodate a 9-ha plot; (3) were of similar overstorey composition; (4) were flat with slope less than 5% to minimise influences on woody fuel alignment (Keane *et al.* 2012*b*); (4) were accessible within 2.5 km of a road; and (5) had similar pretreatment tree size, density, basal area and soil parent material. From the list of potential sampling locations that met our requirements, we randomly selected six locations. Our sampling locations ranged in elevation from 2000 to 2800 m, covering the regional elevational distribution of ponderosa pine forests and capturing the range of forest compositions typical within the region (Fig. 1; Table 1; Peet 1981; Dick-Peddie 1993). Each of the stands was estimated to have become established ~80 years before sampling, following harvesting for railroad and mining supplies, but a remnant older cohort was present in each of the stands.

Within each of the six sampling locations, we established two 9-ha plots, one in the untreated fire-excluded stand and the other in either a fire-excluded stand that had recently been mechanically thinned or mechanically thinned and burned, hereafter referred to as thinned and thinned and burned respectively. Each of the treatments followed two regional silvicultural objectives. The first was to modify stand structure to reduce fire hazard and the second was to create conditions characteristic of a mixed-severity disturbance regime (Underhill *et al.* 2014). Although the exact silvicultural prescriptions varied among sampling locations, all treated stands utilised a cut-to-length system that thinned across crown classes and resulted in variable residual tree densities. Thinned and burned stands were subjected to the same treatments as thinned stands, but in addition, were prescribed-burned using strip head fires. Thinned stands were treated 3 years before fuels sampling; however, given local constraints regarding the use of prescribed fire, only thinned and burned stands that were treated 6 to 8 years before sampling met our selection criteria. These slight differences in treatment age were not considered within our analysis as decomposition rates within ponderosa pine forests of the southern Rocky Mountains are much slower than in many other systems, with average

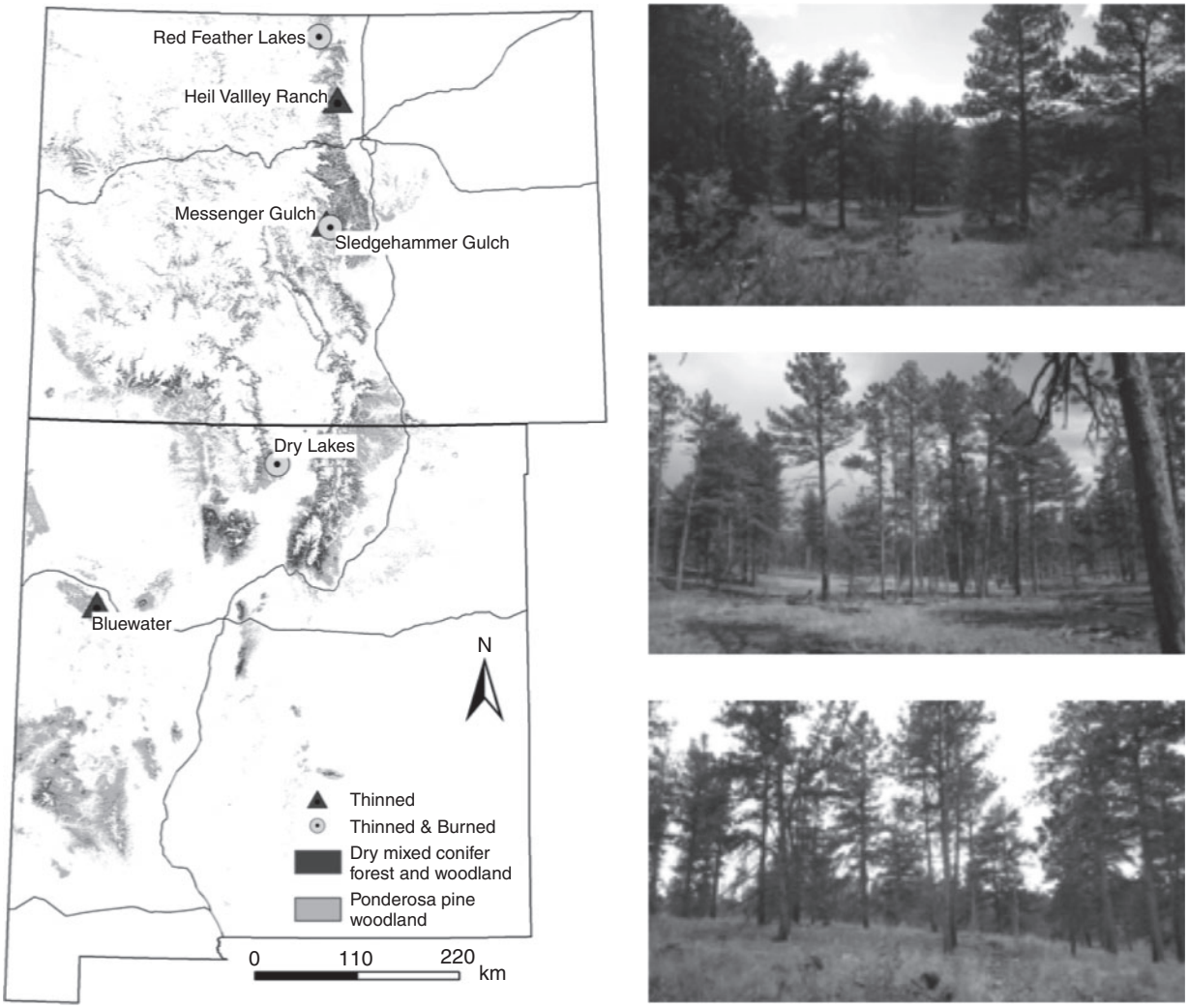

Fig. 1. Location of the six ponderosa pine-dominated study locations across the southern Rocky Mountains used in this study. Each treated stand location was paired with an unmanaged adjacent site. Images from top to bottom show examples of untreated, thinned, and a thinned and burned stand.

Table 1. General description of study sites within the ponderosa pine forest system of the southern Rocky Mountains

Values in parentheses represent standard deviation at variable-radius plot level. Species composition is given by percentage basal area. QMD, quadratic mean diameter; BA, basal area; PIPO, ponderosa pine; PIED, two-needle pinyon; PSME, Douglas-fir; POTR, quaking aspen; QUGA, Gambel oak

Site	Treatment	QMD (cm)	Tree height (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%) PIED (8%)
Messenger Gulch	Untreated	41.8 (11.8)	13.9 (2.6)	14 (9)	301 (479)	PIPO (87%) PSME (11%)
	Thinned	36.7 (7.5)	15.2 (2.2)	10 (6)	173 (208)	PIPO (96%) PSME (4%)
Red Feather	Untreated	34.6 (12.5)	11.8 (2.9)	10 (8)	353 (561)	PIPO (80%) PSME (12%)
	Thinned and burned	33.7 (10.2)	11.6 (2.5)	7 (4)	141 (200)	PIPO (96%) PSME (4%)
Dry Lakes	Untreated	41.2 (10.5)	12.2 (3.1)	12 (8)	534 (870)	PIPO (84%) QUGA (12%)
	Thinned and burned	37.2 (8.0)	13.2 (2.6)	11 (8)	161 (121)	PIPO (98%) QUGA (1%)
Sledgehammer Gulch	Untreated	34.7 (9.8)	12.1 (2.9)	16 (9)	670 (1100)	PIPO (72%) POTR (13%)
	Thinned and burned	33.5 (12.0)	12.6 (4.0)	6 (4)	554 (1520)	PIPO (83%) POTR (11%)

coarse woody debris turnover times of 340 years (Kueppers *et al.* 2004). Alterations to stand density and surface fuels following treatment exhibit a similar pattern to those reported in other studies (Fulé *et al.* 2012). Thinned stands had on average 45% lower stand density and minimal differences in total surface fuel load compared with untreated stands. Thinned and burned stands had on average 45 and 50% lower stand density and total surface fuel load compared with untreated stands respectively (Table 1, Table 2). A detailed description of surface fuel load by fuel type and component for each treatment is reported in Table 2.

Fuel sampling methods

To determine variability and spatial autocorrelation of surface fuel load by fuel type and component (Table 3) within each 9-ha (300 × 300-m) plot, we utilised a nested cluster sampling design similar to Keane *et al.* (2012*b*) (Fig. 2). Within each 300 × 300-m plot, we established four 150 × 150-m quadrants. At the centre of each quadrant, we established three nested grids of sampling locations: 50 × 50, 25 × 25 and 7 × 7 m (Fig. 2). Sampling locations (macroplot, subplot and microplot) were placed at the corners of each quadrant and at the corners of the 50- and 25-m sampling grids, and throughout the 7 × 7-m intensive grid (Fig. 2). This sampling design resulted in a range of separation distances between sampling locations for each fuel type and component, covering the range of reported spatial autocorrelation scales for western ecosystems (Keane *et al.* 2012*b*). Following Keane *et al.* (2012*b*), we only sampled surface fuel loads for components that are the common inputs to fire behaviour and effects models (Table 3). Therefore, loadings for other fuel components such as pine cones, squirrel middens and stumps were not included in the present study.

Within each of the 9-ha stands, we established macroplots at the corners of the four 150 × 150-m quadrants and at the corners of the 50- and 25-m square grids resulting in 41 macroplot sampling locations with separation distances ranging from 25 to 424 m (Fig. 2). At the centre of each macroplot sampling location, we characterised overstorey forest structure within a variable radius plot and measured 1000-h fuel load on a 200-m^2 circular plot (Fig. 2). Variable radius plots were established using either a 2.3- or 4.6-m^2 ha^{-1} basal area factor (BAF) prism. For all live trees at least 1.4 m tall within the variable radius plot, we measured tree height (m), diameter at breast height (diameter at 1.4 m above ground, cm) and crown base height (m), and recorded the species. For all 1000-h fuel particles within the 200-m^2 circular plots, we recorded species and decay class (sound or rotten), and measured length (m) and diameters (m) at both small and large ends. For fuel particles that extended outside the plot, particle diameters were recorded at the plot edge and length was measured for the portion of the particle within the plot. The volume of the fuel particle was then calculated as a conical frustum (Eqn 1).

$$V = \frac{1}{3}\pi\left(R_1^2 + R_1R_2 + R_2^2\right)L \quad (1)$$

where V is the volume of the fuel particle (m^3), R_1 and R_2 are the small- and large-end diameters (m) respectively and L is the length of the fuel particle (m). The mass of each 1000-h fuel particle was then estimated by multiplying the volume by a species-specific particle density accounting for decay class (Harmon *et al.* 2008). To estimate the fuel load for each macroplot, we summed the mass of each fuel particle and divided by the area.

Subplots of 1 m^2 were established at the four corners of the 50- and 25-m square grids, and located throughout the 7 × 7-m intensive grid, resulting in 228 subplots with separation distances ranging from 1 to 283 m (Fig. 2). At each subplot 1-, 10- and 100-h dead down woody fuel loadings were inventoried

Table 2. Mean and standard deviation of loading by fuel component and treatment type for ponderosa pine forests of the southern Rocky Mountains

Fuel component	Average loading (kg m^{-2}) (s.d.)		
Time-lag class	Untreated	Thinned	Thinned and burned
1-h	0.049 (0.081)	0.047 (0.072)	0.036 (0.055)
10-h	0.123 (0.204)	0.270 (0.421)	0.118 (0.171)
100-h	0.093 (0.234)	0.249 (0.591)	0.141 (0.310)
1000-h	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 forest floor	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

Table 3. Description of the eight surface fuel types and components sampled in this study

Fuel type	Fuel component	Particle size	Description
Dead down woody	1-h	<0.64-cm (0.25-inch) diameter	Detached woody fuel particles on the ground
	10-h	0.64–2.54-cm (0.25–1.0-inch) diameter	
	100-h	2.54–7.62-cm (1–3-inch) diameter	
	1000-h	>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 necromass

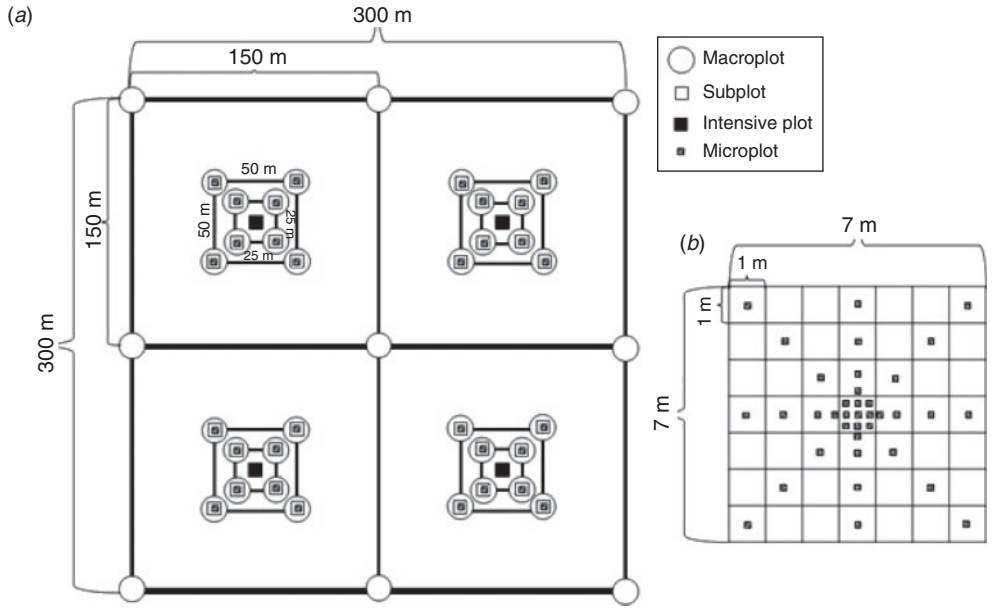

Fig. 2. Each site was inventoried using a nested cluster sampling design (*a*) that included 41 macroplots, 32 subplots and 4 intensive plots. At each macroplot ,variable-radius plots were used to measure the overstorey and 200-m^2 fixed-radius circular plots were used to sample 1000-h fuels. Each subplot included a 1-m^2 quadrat for sampling live herbaceous and shrub and dead down woody fuels and a 0.09-m^2 frame for sampling litter and duff. Within each 7 × 7-m intensive plot (*b*), live herbaceous and shrub and dead down 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 in $n = 41$ overstorey and 1000-h fuel samples, $n = 228$ live herbaceous, shrub and dead down woody fuel samples, and $n = 180$ litter and duff fuel samples at each site.

using the photoload method (Keane and Dickinson 2007). The photoload sampling technique requires the user to visually estimate fuel loading by size classes from a reference set of downward-facing photographs that contain graduated levels of fuel loading. Similarly to Keane *et al.* (2012*b*), we utilised the photoload method because it is easy, fast and consistent when users are trained properly (Sikkink and Keane 2008); however, because it is a visual method, it can introduce potential errors and bias into fuel load estimates. To overcome these potential sources of error, we randomly chose 20% ($n = 48$) of all subplots for destructive sampling. On the destructively sampled plots, all 1-, 10- and 100-h fuels were collected, sorted on site and placed in separate paper bags for transport back to the laboratory where they were dried and weighed to determine the actual fuel loading in the subplot. In cases where a fuel particle was only partially within the subplot, only the portion of the fuel particle within the plot was collected. We then developed linear regressions between the visual estimates and actual fuel load for each particle size, site and observer combination and used the slope of the regression line to correct the remaining visually estimated fuel loads at each subplot. As shown by Tinkham *et al.* (2016*b*), a 20% double sampling rate with regression estimation can substantially improve sample bias and precision associated with the photoload method. Within each subplot, we clipped and sorted all herbaceous and shrub fuels by their respective fuel components into paper bags for transport back to the laboratory to be dried and weighed.

Litter and duff fuel loads were estimated on 180 0.09-m^2 microplots. Thirty-two of the microplots were nested within the subplots at the corners of the 50- and 25-m square grids whereas the remainder were nested within subplots located in the 7 × 7-m intensive grid (Fig. 2); separation distances ranged from 0.35 to 283 m. At each microplot, all litter and duff fuels were placed in separate paper bags and transported to the laboratory to be dried and weighed. Litter and duff loading was calculated by dividing the dry weight of the extracted material by the area. Following Keane (2015), we defined litter as freshly fallen, readily identifiable non-woody plant necromass, and duff 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. Therefore, our litter layer includes the O_i soil horizon and duff contains the remainder of the *O* horizon, including the *Oe* and *Oa* horizons (Frandsen 1987; Schoeneberger *et al.* 2012).

Data analysis

To determine the scale of spatial autocorrelation and variability of fuel load in each treatment type, semivariogram analysis was performed following the approach outlined in Webster and Oliver (2007) (Fig. 3). Semivariograms present a graphical representation of the spatial continuity of a dataset by calculating the variance between all pairs of measured sample points as a function of their separation or lag distance. Semivariogram models are interpreted based on three modelled parameters: the range, sill and nugget (Fig. 3). The range is estimated as the point along the *x* axis where the modelled curve flattens. Points located next to each other at scales below the range are spatially autocorrelated, whereas points spaced at distances larger than

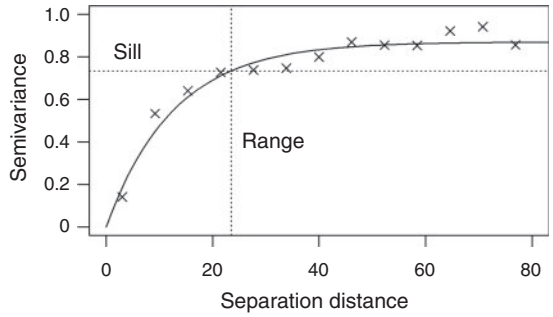

Fig. 3. Elements of a semivariogram fitted to theoretical data. The range is the separation distance at which the modelled curve flattens, and is an estimate of the characteristic length scale of a spatial process, representing the scale at which the process or characteristic is best described. The corresponding *y* axis value along the modelled curve at the range is called the sill, and represents the maximum variation of the process.

the range are spatially independent. The range value provides an estimate of the scale at which spatial autocorrelation occurs and represents the scale at which the fuel component is best described and measured. The corresponding *y* axis value along the modelled 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 that displays no spatial autocorrelation.

We grouped lag-distances of all pairs of measured sample points into 1-m bins and combined the site-level pairs within each treatment type to generate empirical semivariograms. For each treatment type, an exponential semivariogram was fitted to all pairs up to a lag distance of 200 m using maximum likelihood estimators utilising the GeoR and mvtnorm statistical packages in *R* (Ribeiro and Diggle 2012; Genz *et al.* 2014). This lag distance represented ~50 and 70% of the maximum lag distance at each site for the 1000-h fuel load and all other fuel loads respectively. Fitted models were visually inspected 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.

To evaluate if differences existed among the modelled treatment sill and range values, we compared the modelled range and sill values among treatments using a series of two-sample Z-tests (Eqn 2).

$$Z = \frac{\sigma_1 - \sigma_2}{\sqrt{(\mathrm{SE}_1^2 + \mathrm{SE}_2^2)}} \quad (2)$$

where σ is the estimated parameter and SE is the estimated standard error from the modelled exponential semivariogram. We then compared the modelled range and sill value across all treatments using a Bonferroni correction to maintain an overall α of 0.05. Because maximum likelihood estimators are normally distributed and all pairs within a treatment were used, all statistical tests met assumptions of normality and had sufficiently large sample sizes to utilise a two-sample Z-test for comparisons.

In addition to evaluating differences in modelled semivariogram parameters among treatments, we also developed two scaling relationships of the modelled semivariance and range to more easily measured fuel bed attributes using power-law functions (Eqn 3):

$$Y = ax^b \quad (3)$$

where *x* is the independent variable, *Y* is the dependent variable, *a* is a normalisation constant and *b* is the scaling exponent. Power-law functions were used in part because they 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 (Stanley *et al.* 2000; Gisiger 2001). Second, 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). Based on the findings of Keane *et al.* (2012*b*), we first developed a scaling relationship using the modelled range as the dependent variable and the diameter of all surface fuel components as the independent variable.

Following Keane *et al.* (2012*b*), we estimated the 1-, 10- and 100-h dead down woody fuel component diameters as the midpoint of the size classes; litter and duff diameters were estimated as 0.2 cm, and the 1000-h dead down woody fuel components were divided into three classes (7.6–11, 11–16, 16–maximum cm), of which the midpoints were used in the analysis ($n = 24$, but three site-level fuel components produced pure nugget models, leaving 21 points for analysis). Dividing 1000-h fuels into three size classes provided a more representative way of defining particle diameter for these fuels instead of a function driven by one outlying point for this size category and created a more evenly distributed set of *x* values. Additionally, we investigated the relationships between the modelled semivariance of fuel loading and the mean fuel load across all size classes using a power-law function (Eqn 3). Based on Taylor (1961), we expect that the variance of a natural population is proportional to a power of the population mean, and thus higher fuel loads will be associated with increased variance.

Results

Our modelled sill values suggest that surface fuel components are highly variable across treatment types (Table 4). In addition to the large sill values from our semivariogram analysis, coefficients of variation were above 100% for all fuel components, which provides additional support to the hypothesis that fuels are highly variable in ponderosa pine forests of the southern Rocky Mountains. Duff fuels had the largest modelled sill regardless of treatment whereas 1-h dead down woody fuels tended to have the lowest sill values (Table 4). The only exception to this trend was in thinned stands where herbaceous

Table 4. Variogram model fits by fuel component and treatment type in ponderosa pine forests of the southern Rocky Mountains

Values in parentheses represent standard errors and grey cells indicate fuel components where semivariogram maximum likelihood could not be fitted. Means followed by different lowercase letters in each column indicate significant differences ($\alpha = 0.05$) identified using the two-sample Z-test among treatments for each fuel component

Fuel component	Treatment	Sill (kg m^{-2})^2	Range (m)
1-h	Untreated	0.0254 (0.0030)^a	14.50 (1.88)^a
	Thinned	0.0054 (0.0003)^b	0.91 (0.11)^b
	Thinned and burned	0.0041 (0.0003)^c	1.81 (0.22)^c
10-h	Untreated	0.0403 (0.0022)^a	1.47 (0.11)^a
	Thinned	0.1586 (0.0114)^b	1.32 (0.13)^a
	Thinned and burned	0.0331 (0.0030)^a	1.44 (0.20)^a
100-h	Untreated	0.0558 (0.0026)^a	0.89 (0.07)^a
	Thinned	0.3226 (0.0249)^b	1.53 (0.15)^b
	Thinned and burned	0.0777 (0.0051)^c	1.23 (0.10)^b
1000-h	Untreated[A]	0.3998 (0.0418)^a	
	Thinned	0.3026 (0.0579)^a	47.59 (13.10)^b
	Thinned and burned	0.3558 (0.0686)^a	46.89 (13.21)^b
Litter	Untreated	0.4789 (0.0255)^a	1.13 (0.08)^a
	Thinned	0.5518 (0.0398)^a	0.93 (0.11)^a
	Thinned and burned	0.1701 (0.0136)^b	0.99 (0.12)^a
Duff	Untreated	5.9616 (0.3165)^a	1.18 (0.08)^a
	Thinned	5.1888 (0.3857)^a	1.02 (0.10)^a
	Thinned and burned	0.9112 (0.0744)^b	1.16 (0.13)^a
Shrub	Untreated[A]	0.0717 (0.0002)	
	Thinned[B]		
	Thinned and burned	0.0133 (0.0008)	1.00 (0.09)
Herbaceous	Untreated[B]		
	Thinned[A]	0.0041 (0.0002)	
	Thinned and burned[B]		

[A]Pure nugget model; value given in sill column is nugget value.
[B]Maximum likelihood estimate fit not possible owing to distribution of data.

fuels had a lower sill value than 1-h dead down woody fuels. Within the dead down woody fuel type, sill values tended to increase with increasing size class, with 1000-h fuels having the largest modelled sill values, followed by 100-, 10- and 1-h fuels (Table 4). Modelled range values varied across fuel components from less than 1 to 47 m. Litter, duff, shrub, herbaceous, and 1-, 10- and 100-h dead down woody fuels all had ranges less than 2 m with the exception of the untreated 1-h fuels, which had a range of 14 m (Table 4, Fig. 4). The modelled range values were greatest for 1000-h fuels, averaging ~47 m for the thinned and thinned and burned sites (Fig. 4). For 1000-h dead down woody fuels in untreated sites, our analysis produced a pure nugget model, indicating that either the range is below 25 m (i.e. the minimum tested lag distance) or there is complete spatial randomness.

Treatments had inconsistent effects on the modelled sill values across fuel types and components. For the litter and duff fuel components, we found no differences in the modelled sill between untreated and thinned stands (Fig. 5, Table 4). However, thinned and burned stands had a significantly lower sill than either untreated or thinned stands (Fig. 5, Table 4). Changes in dead down woody fuel sills following treatment exhibited no clear pattern across fuel components. The sill of 1-h dead down woody fuel components was significantly greater in untreated stands compared with both thinned and thinned and burned stands and was greater in thinned stands compared with thinned and burned stands. Untreated stands had a lower 10-h dead down woody sill compared with thinned stands but were not different from thinned and burned stands (Fig. 5, Table 4). Untreated stands had the lowest 100-h dead down woody fuel sill of all treatment types, whereas 100-h dead down woody sill on thinned stands was significantly greater than the other treatment types (Table 4, Fig. 5). We found no differences in 1000-h dead down woody sills across treatments.

Estimated variogram range values for litter and duff were similar among treatments (Table 4, Fig. 4). However, both treatment types resulted in a decrease to range values for 1-h dead down woody fuels and an increase in the range for 100-h dead down woody fuels compared with untreated stands (Table 4, Fig. 4). Estimated 1-h dead down woody fuel range values were also greater in thinned and burned stands compared with thinned stands, but there were no differences in 100-h dead down woody range values between these two treatments (Table 4, Fig. 4). We found no significant differences among treatments for 10-h dead down woody fuel ranges across all treatment types. In terms of 1000-h dead down woody fuels, we found no differences between thinned and thinned and burned stands. In untreated sites, our analysis indicated a pure nugget model, which suggests that these sites are spatially autocorrelated at scales below our minimum lag distance of 25 m.

Owing to zero-inflated and extremely right-skewed data, we were unable to produce maximum likelihood estimates for shrub and herbaceous fuel types across all treatments and therefore we did not make pairwise comparisons across treatment types for these fuel components.

We found that the sill values scale as a function of total fuel load following a power-law function:

$$Sill = 1.862 \times load^{1.742} \quad (4)$$

where *load* is the fuel load in kilograms per square metre ($R^2 = 0.99$, root-mean-square error (RMSE) = 0.152; Fig. 6). The scaling factor of 1.7 (95% confidence interval (CI) 1.38–1.92) suggests that the fuel load variability increases more rapidly than average site-level loading and that a doubling of fuel load results in a 3.3-fold increase in variability. In addition, we found that the estimated range (m) scales as a function of the diameter of fuel particles (d, cm) following a power-law function:

$$Range = 0.217 \times d^{1.839} \quad (5)$$

This relationship ($R^2 = 0.88$, RMSE = 5.371, $b = 1.839$, 95% CI 1.050–2.627; Fig. 7) suggests that smaller-diameter fuel particles will be spatially autocorrelated at short distances whereas larger diameter fuel particles will exhibit spatial autocorrelation across greater distances.

Discussion

Surface fuel loadings in southern Rocky Mountain ponderosa pine forests are highly variable across and within surface fuel

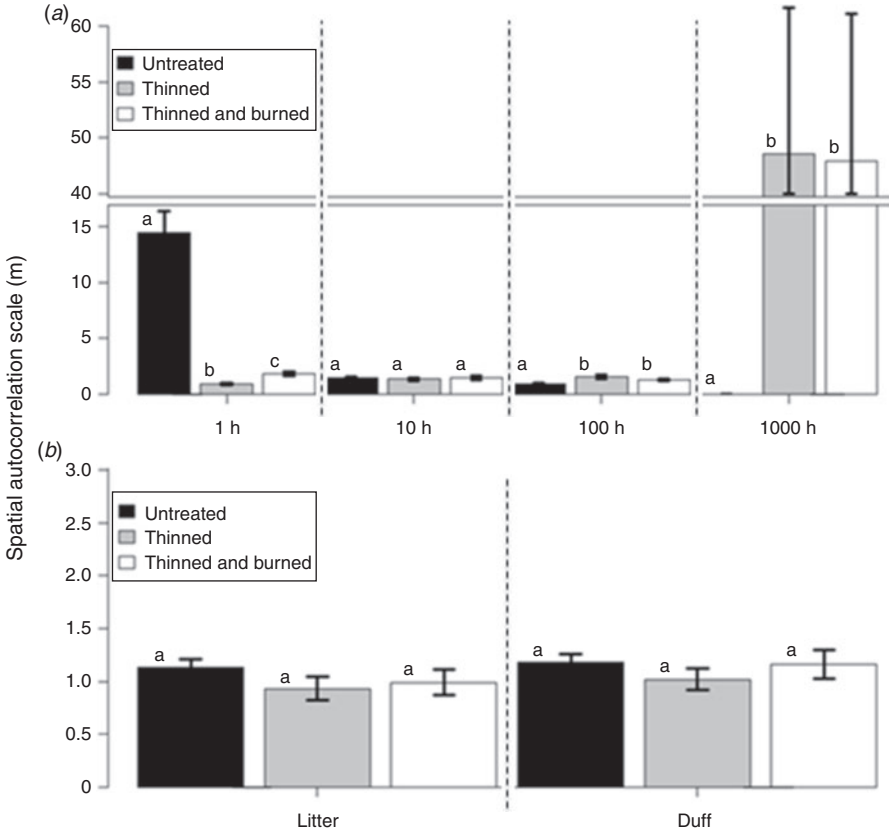

Fig. 4. Semivariance with standard errors for (*a*) dead down woody fuels; and (*b*) litter and duff fuels by treatment type in ponderosa pine forests of the southern Rocky Mountains. Letters represent significant differences ($\alpha = 0.05$).

types and components. High spatial variability in surface fuel loads has also been identified in several northern Rocky Mountain forest and rangeland systems and in south-eastern US pine ecosystems (Brown and Bevins 1986; Hiers *et al.* 2009; Keane *et al.* 2012*b*). In the present study, we found that variability increased as a function of mean fuel load following a power-law relationship with an exponent of 1.742, indicating that a doubling in fuel load will result in a 3.3-fold increase in the variability. To our knowledge, no other studies have developed scaling relationships between the variance and mean fuel load and thus it is unknown if these scaling functions are consistent across a wide range of environmental conditions and ecosystems. Previous studies have suggested that variability in surface fuels arises owing to complex interactions among the distribution of plants, the deposition and decomposition of fuel, and disturbances through time and space (Keane *et al.* 2012*b*; Keane 2015). In addition, several authors have suggested that power-law relationships can arise owing to random sampling of highly skewed populations and vary across scales of observation (Hanski 1987; Sawyer 1989; Yamamura 1990; Cohen and Xu 2015). Further development of scaling functions across a range of the parameters thought to influence fuel loads and spatial scales could help identify emergent properties of wildland fuel beds and provide insights into the underlying mechanisms that influence fuel load variability.

In addition, we found that the estimated range was variable across fuel components ranging from <1 to 48 m. When compared with duff fuel spatial aggregation in longleaf pine of Florida, USA, similar fine-scale aggregation (~1 m) is seen (Kreye *et al.* 2014). However, our findings for duff spatial-scale of autocorrelation differ greatly from the results of Robichaud and Miller (1999), who found a range value of 65 m for duff depth in mixed-conifer forests of Montana, USA. This large difference may be partially explained by the differences in sampling, with Robichaud and Miller (1999) sampling on a 30-m grid that resulted in their smallest lag-bin for analysis being ~20 m.

Our results indicate that the scale of spatial autocorrelation increases as a function of fuel component diameter following a power-law relationship. This scaling relationship suggests that smaller-diameter fuel particles will have fine-scale spatial autocorrelation and larger-diameter fuels have coarser-scale spatial autocorrelation: a doubling of fuel particle diameter resulted in a 3.6-fold increase in spatial autocorrelation length scale. This scaling relationship shows broad agreement with results reported by Keane *et al.* (2012*b*); however, the trend reported by Keane *et al.* (2012*b*) would suggest larger range values for small-diameter fuel particles and similar range values for larger-diameter fuel particles compared with our analysis. Keane *et al.* (2012*b*) found considerable variability in the parameters of the scaling relationships across ecosystems.

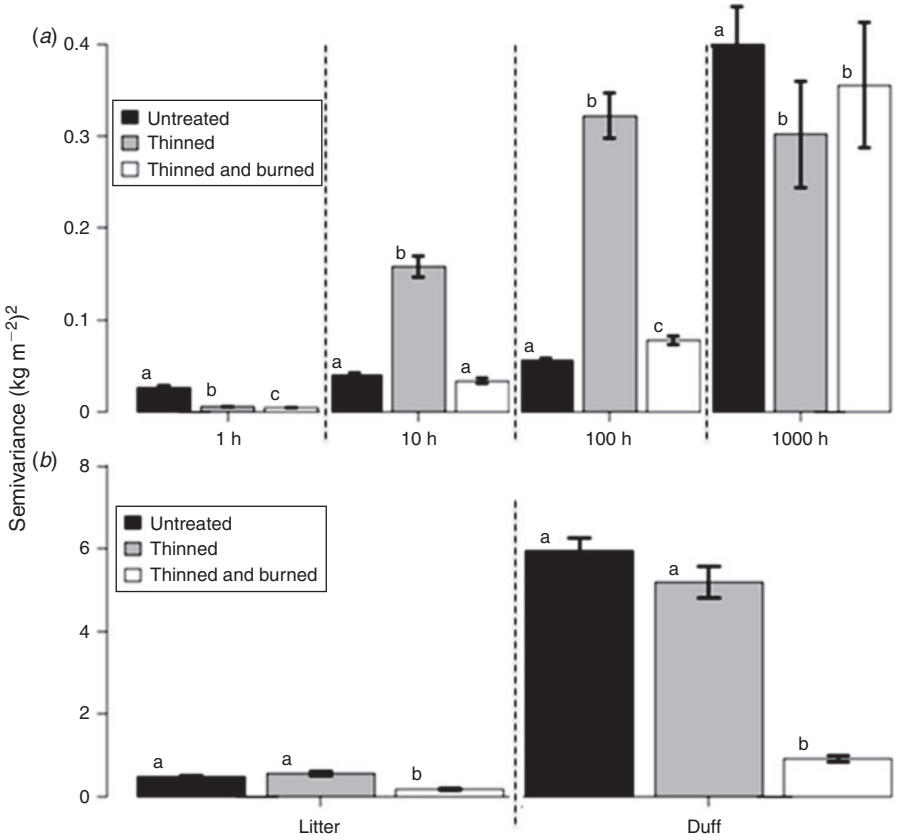

Fig. 5. Spatial autocorrelation scale values with standard errors for (*a*) dead down woody fuels; and (*b*) litter and duff fuels by treatment type in ponderosa pine forests of the southern Rocky Mountains. Letters represent significant differences ($\alpha = 0.05$).

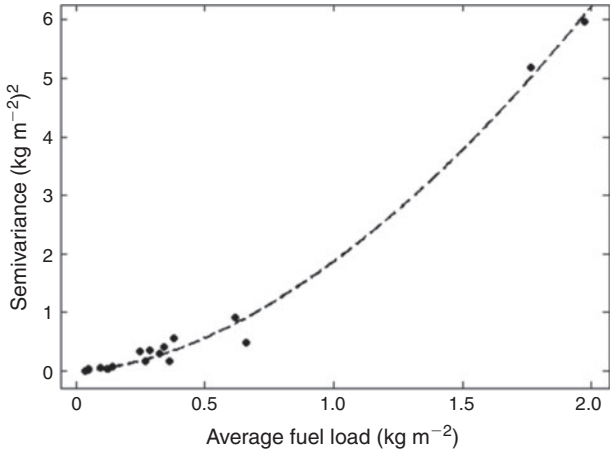

Fig. 6. Relationship between stand-level mean fuel component loading and semivariance ($R^2 = 0.99$, root-mean-square error (RMSE) = 0.152).

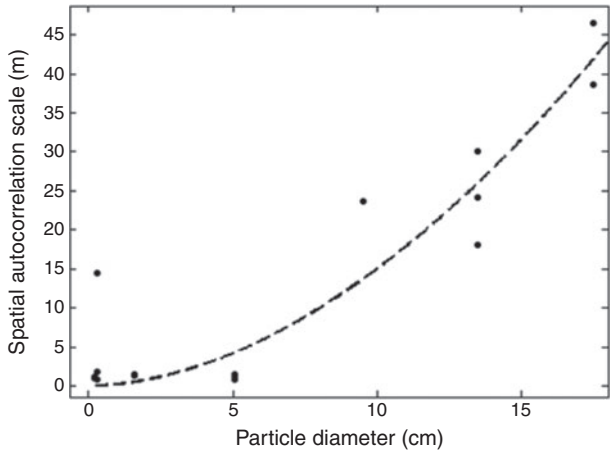

Fig. 7. Relationship between average particle diameter within each fuel component and spatial autocorrelation scale ($R^2 = 0.88$, root-mean-square error (RMSE) = 5.371).

Further research across ecosystems and gradients could provide insights into the controls of these relationships and the key processes influencing spatial autocorrelation of surface fuels. For example, additional investigation into the normalisation parameter could help identify fundamental constraints on the system imposed by different environments and productivities (Brown *et al.* 2002), whereas additional comparisons of the scaling exponent may indicate differences among ecosystems.

Both thinned and thinned and burned treatments seemed to alter two components of fuel heterogeneity: spatial autocorrelation length scale and variability of fuel load. However, the effect

of treatments on heterogeneity was inconsistent among fuel components, with these differences possibly arising for a variety of reasons. First, the preferential removal or death of certain trees during thinning and prescribed-fire activities may disproportionately influence fuel components because branch diameter size distributions differ by species and position in the canopy (Brown 1978). In addition, complex spatial and temporal interactions between the pretreatment stand characteristics and patterns of treatment disturbance may ultimately control spatial arrangement and distribution of wildland fuels. Within this study, we did not address the varying time since treatment as coarse woody debris within these systems have been documented as having average turn over times of 340 years (Kueppers *et al.* 2004). However, in systems with much faster decomposition rates (e.g. coastal Douglas-fir), the time since treatment will undoubtedly play an important role in determining the effect of fuels treatments on the spatial arrangement and distribution of wildland fuels. Finally, as suggested by Keane *et al.* (2012*b*), the use of uneven size classes in sampling woody fuels may introduce additional uncertainty into fuel load estimates. The combination of these factors potentially complicates the detection of consistent treatment differences.

Our findings provide insight that could help address several fuels management and ecological questions by informing the approaches used in fuels inventory, fuel mapping, and fire behaviour and effects modelling. One of the key findings from our study is that surface fuels vary at fine spatial scales, which has potentially important implications for understanding the processes driving scales of spatial variability. As suggested by Carlile *et al.* (1989) and Keane *et al.* (2012*b*), the most appropriate resolution to sample any process for capturing its true variance will correspond to the inherent spatial scale of the population. Utilising our modelled range parameters, characterisation of spatial variability for 1-, 10- and 100-h fuel components should be conducted on fixed areas that encompass between 1 and 210 m^2 whereas 1000-h fuels would best be characterised on areas of ~2300 m^2 for ponderosa pine forests of the southern Rocky Mountains (Table 4). Given the potential sampling effort required at these plot sizes, the use of subsampling or a cluster sampling design that occupies these scales may provide a practical alternative for characterising the variability of surface fuels. However, additional research that investigates the required number of subsamples to achieve a given level of accuracy at the plot level is needed. Alternatively, line-intercept sampling could be conducted where 1-, 10- and 100-h fuels are sampled on transect lengths equal to the estimated range parameters identified (van Wagner 1968). Regardless of future developments in fuel measurement techniques, the implementation of sampling strategies that capture the inherent scale of variability would allow increased understanding of the processes driving spatial and temporal dynamics of fuels.

In addition, our results suggest that each wildland fuel component not only varies at a unique scale but also exhibits a different level of population variance. These findings indicate that optimal fuel inventory approaches may need to adopt different sampling strategies for each fuel component. Keane *et al.* (2012*b*) suggested that a hierarchically nested sampling design where each fuel component is measured within differently sized plots corresponding to the estimated range parameter would be a logical approach to designing a fuels inventory. A fully optimised sampling design would take this a step further and also allow the intensity or number of samples to vary for each fuel component. To advance fuels inventory approaches focused on quantifying treatment effects, fuels managers may need to account for fuel component differences when determining optimal plot sizes and sampling intensities. Regardless of the sampling intention, fuels sampling designs should justify their sampling scale according to the inherent spatial scale of the population (i.e. range); this will be the only way to begin accurately capturing and representing the spatial variability within surface fuel loading. However, such designs may be very costly to implement and therefore fuels managers may choose to compromise and sample all fuel components at each location, leading to oversampling of some components.

Fuel maps have become a pivotal tool within fire and fuels management, but most commonly are produced at resolutions (i.e. 30 m) that fail to capture the natural variation of wildland fuels. The scale at which we sample is known to have a profound effect on a variable's distribution and influence ecological inferences drawn from analysis (Horne and Schneider 1995; Dungan *et al.* 2002). Developing fuel maps at the inherent scale of fuel spatial variability could provide insights into spatially dependent management questions such as assessing wildlife habitat or estimating the risk and hazard of spruce beetle outbreaks (Reynolds and Holsten 1994; Bate *et al.* 2004).

Incorporating surface fuel variability into fire modelling may be an important step in linking fire behaviour and effects to fuel loading distributions (Thaxton and Platt 2006; Hiers *et al.* 2009; Keane *et al.* 2012*b*). Previous studies have demonstrated how fine-scale variations in fuel loading can have significant implications for fire spread and intensity (Cheney and Gould 1995; Fernandes *et al.* 2004; Hoffman *et al.* 2012) as well as on the subsequent post-fire plant response and residue composition (Brewer *et al.* 2013; Smith *et al.* 2016). Most fire behaviour and effects models are empirically derived relationships between coarse-scale fire behaviour and mean fuel bed and environmental conditions, and therefore do not account for fine-scale variability when predicting fire behaviour or effects (Reeves *et al.* 2009; Hoffman *et al.* 2016). Although most fire behaviour and effects models used in fire management do not currently account for fuel variability, newer models such as the Wildland–Urban Interface Fire Dynamics Simulator (Mell *et al.* 2007, 2009) and FIRETEC (Linn *et al.* 2002, 2005) are capable of representing fuels in 3-dimensional space and thus can account for the inherent spatial scales of fuels. However, these models have not yet been used to explore the implications of surface fuel variability on potential fire behaviour partially owing to a lack of approaches capable of generating spatially explicit fuel model maps. Development of these new fuel mapping approaches would foster joint field and simulation modelling studies that would allow a deeper understanding of the relationship between fuel patterns and process.

Conclusion

Although quantifying heterogeneity has been an ongoing objective in ecological sciences for several decades (Patil *et al.* 1971; Pielou 1977), only recently has it received considerable recognition in determining wildland fire behaviour and effects

(Cheney and Gould 1995; Fernandes *et al.* 2000; Hoffman *et al.* 2012, 2105; Cruz and Alexander 2013; Keane *et al.* 2012*b*). The present study is one of the first attempts to quantify surface fuel spatial autocorrelation and semivariance in dry forest types of the western US and the only study that has attempted to assess the effects of forest management on surface fuel spatial autocorrelation and semivariance. Our results indicate that surface fuel loadings are highly variable at fine spatial scales for all but the largest fuel components measured. Additionally, we found that the sill and range varied among fuel components and that treatments can affect these measures of spatial heterogeneity. These findings suggest that optimising fuels sampling could best be achieved by designing protocols where sample scales correspond to the spatial scale of autocorrelation of individual fuel components. Although our results provide insights into the spatial dynamics of surface fuels in southern Rocky Mountain ponderosa pine forests, additional research that spans ecological and geographic gradients is needed to further develop our understanding of fuel dynamics. Fully understanding the processes that lead to these scales of spatial variation in fuel loading holds potential to advance the assessment of wildlife habitat, the techniques used for mapping fuels and our ability to model the linkages between fuel loading and fire behaviour and effects.

Acknowledgements

This research was supported in part by funds through Joint Fire Science Program Project 13–1-04–53, in part by funds provided by the Rocky Mountain Research Station, Forest Service, USDA, and the National Fire Plan 13-JV-11221633–058 and in part through the USDA National Institute of Food and Agriculture McIntire–Stennis Program. We would also like to thank Monique Rocca for providing feedback on an earlier version of this manuscript; Daniel Cooley and Robin Reich for assistance with spatial statistics; and Claire Gribenow, William Grimsley, Carrie Howard, Larry Huseman, Mason Knuthson, Peter Morin, Sarah Newton, Donn Slusher, Andrew Spencer, Brianna Stone, Cameron Taylor and Justin Ziegler for their help with field data collection and sample processing.

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