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A surface fuel classification for estimating fire effects[1]

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Abstract. We present a classification of duff, litter, fine woody debris, and logs that can be used to stratify a project area into sites with fuel loading that yield significantly different emissions and maximum soil surface temperature. Total particulate matter smaller than 2.5 μm in diameter and maximum soil surface temperature were simulated using the First Order Fire Effects Model. Simulation results were clustered into 10 Effects Groups using an agglomerative routine where each Effects Group defined a unique range of soil temperature and emissions. Classification tree analysis was used to estimate the critical duff, litter, fine woody debris, and log loadings associated with the soil temperature and emissions of each Effects Group. The resulting 21 fuel classes are called Fuel Loading Models and classified the study dataset with an ~34% misclassification rate. The classification can be used to describe fuel loadings for a plot or stand, or as map units for mapping fuel loadings across large regions. The classification process can be used to develop finer-scale fuel classifications for specific regions or ecosystems.

Additional keywords: fuel loading, fuel mapping, simulation modeling, smoke, soil temperature.

Introduction

Wildland fuel classifications are critical to fire management because they provide a simple way to input extensive fuel characteristics into complicated fire behavior and fire effects computer models (Anderson 1982; Ottmar *et al*. 2007). Fuel classifications synthesize fuel attributes required by fire computer models into a finite set of classes or categories that ideally represent all possible fuelbeds for a region and their subsequent fire behavior and effects (Burgan and Rothermel 1984; Sandberg *et al*. 2001). These classification categories can also be used as (1) map units to spatially simulate fire dynamics (Keane *et al*. 2001; McKenzie *et al*. 2007); (2) a simple fuels inventory system for quantifying biomass and carbon stocks (Taylor and Sherman 1996); and (3) an indirect measure of fire hazard and risk (Sandberg *et al*. 2001; Ottmar *et al*. 2007).

Total particulate matter 2.5 μm and less in aerodynamic diameter ($PM_{2.5}$ emissions) and maximum soil surface temperature are two fire effects important to managers. The US Environmental Protection Agency, through its state partners, monitors $PM_{2.5}$ density to ensure compliance with the Clean Air Act using the National Ambient Air Quality Standards. Wildland fire produces substantial $PM_{2.5}$ emissions; thus fire managers must report estimates of these emissions when conducting prescribed fire. Moreover, other fire effects, primarily those associated with fuel consumption, are directly related to emissions. Soil surface temperature is a major factor used to examine fire's influence on soils. Soil heating modifies the chemical and organic content of soils. Reduced nitrogen availability, soil porosity, infiltration rates, and increased overland flow are examples of possible soil heating effects (DeBano *et al*. 2005). High soil temperatures can lead to the death of plant roots, fungi, and mycorrhizae, many of which grow in the nutrient-rich area near the soil surface at the duff–soil interface (Busse and DeBano 2005).

Fuelbeds are the physical stratification of fuel components and are defined by the individual fire models. Fuelbed classifications used for examining fire effects typically use 'loading' (dry biomass per unit area) as the primary fuel attribute. Fuel load is then reported for each fuelbed component in the classification. Common ground and surface fuelbed components are duff, litter, downed woody material, shrub, and herbaceous fuels. Duff is biomass material decomposed to the point that it is difficult to identify its origins. Litter is the detached and fallen plant material that is still recognizable as plant parts. Downed dead woody fuels are usually stratified by size classes: twigs (1-h, 0–0.6 cm in diameter), branches (10-h, 0.6–2.5 cm diameter), large branches (100-h, 2.5–7.6 cm diameter), and logs (1000-h, >7.6 cm diameter) (Fosberg 1970). In the present study, we define fine woody debris (FWD) as all dead and down woody material less than 7.6 cm diameter (<3 in diameter). Herbaceous plants lack woody stems and have aerial parts that die back at the end of the growing season. Shrubs are woody plants that have axes that do not die back at the end of the growing season. Shrubs may have woody twigs, branches, and large branches, but because these parts are still attached to the main

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plant and generally upright, they are not considered dead and down woody fuels. Shrub and herbaceous fuels may include live and dead material. Crown fuels are another fuelbed component typically defined as fuel >2 m above the ground. Fire behavior fuel classifications, such as fire behavior fuel models, include other attributes (e.g. surface area and heat content) in addition to fuel loading (Anderson 1982).

Most fuel classifications used to predict fire effects use vegetation classifications to assign fuel loadings as inputs to fire models (Shasby *et al.* 1981; Ottmar *et al.* 1994; Hawkes *et al.* 1995; Mark *et al.* 1995; Hardwick *et al.* 1996; Reinhardt and Keane 1998; Hardy *et al.* 2000). Fuel loadings by component are usually summarized across all plots within a vegetation classification category to create average fuelbed characteristics that are then assigned as fuelbed attributes. There are numerous examples using variations of this vegetation-based approach, including the Society of American Foresters cover type classification used in the First Order Fire Effects Model (FOFEM) (Reinhardt *et al*. 1997; Reinhardt and Keane 1998; Mincemoyer 2002), and the potential vegetation type–cover type–structural stage combinations used in a variety of recent mapping efforts (Ottmar *et al*. 1994; Keane *et al*. 1998; Menakis *et al*. 2000; McKenzie *et al*. 2007).

The high variability of fuels across space and time often limits the applicability of vegetation-based approaches (Keane *et al*. 2001; Keane 2008). Fuel loads can be poorly correlated with vegetation characteristics because (1) disturbance history is usually an important predictor of surface fuel loading (Brown and See 1981; Brown and Bevins 1986) but it is difficult to measure in a way that is useful for predicting the load of fuelbed components; (2) fuel classifications based on vegetation often do not identify unique sets of fuel loading because the variability of loadings within a plot can be as great as the variability across the entire vegetation type (Brown and Bevins 1986); (3) summarized fuel loading estimates can be redundant across vegetation classes (Keane *et al*. 1998); and (4) the resolution of the vegetation classification (i.e. plant communities) may not match the resolution needed to describe the fuelbed (Brown and See 1981; Brown and Bevins 1986).

Managers would benefit from a fuel loading classification that incorporates both the spatial variability of fuelbeds and the resolution of the fire models for which the classification will be used. Defining fuels categories based on statistically significant differences in fuel loadings across all fuel components would ensure that each category represents a unique fuelbed. Additionally, if the classification incorporated unique groupings of fire effects, managers would know when a change in a fuel class would indicate significantly different fire effects. This would allow the fuel classification categories to indirectly represent fire hazard measures (Sandberg *et al*. 2001; Hall and Burke 2006).

The objectives of the present study were two-fold: (1) to develop a process for classifying fuelbeds based on fuel loadings and fire effects, and (2) to use this process to develop an initial classification of surface fuels (duff, litter, FWD, and logs) called Fuel Loading Models (FLMs). Owing to data limitations, we only included duff, litter, FWD (twigs, branches, and large branches), and log fuelbed components in this classification. The FLM classification incorporates both the variability of fuel loadings across fuel components and the resolution of a commonly used fire effects prediction model: FOFEM (Reinhardt *et al.* 1997; Reinhardt and Keane 1998; Reinhardt 2003). The classification procedure described can be used to develop new fuels classifications that are specific to an ecosystem, landscape, or regional area, or the procedure can be used to develop classifications for different management objectives using different fire effects simulation models, fuel components, fire effects, and burning conditions. A field guide for the FLM classification with photos and an illustrated key is presented in a companion publication (Sikkink *et al*. 2009).

Methods

Our initial intent in creating a comprehensive fuel classification was to classify the fuels based on loading using cluster analysis. However, preliminary analyses indicated 75% of the fuelbeds clustered into two statistically distinct groups and any attempt to differentiate more groups resulted in a lack of statistical significance between groups. Moreover, we had intended this classification to be used as inputs to fire effects models but many simulated fire effects were similar when using the cluster group median loadings. We noted that we could improve cluster separability and more effectively tune the classification to unique simulated fire effects if we used fire effects as our classification variables.

The FLM classes were developed using the generalized process illustrated in Fig. 1: (1) collect and compile fuelbed data from plots across the contiguous United States; (2) simulate emissions and soil temperature for each plot using FOFEM; (3) cluster simulation results by plot into Effects Groups using fire effects predictions; (4) create FLMs using classification tree analysis to identify critical fuel loadings that led to the Effects Groups; and (5) assess the accuracy of the FLM classification. Each step is detailed below.

Collecting and compiling fuels data

Plot-level surface fuel data were compiled from a wide variety of recent fuel sampling projects conducted across the contiguous United States (less than 100 plots were sampled in Alaska and Hawaii and we did not include them in this study). Data were provided by the: Bureau of Land Management, Bureau of Indian Affairs, Department of Army, Student Conservation Association, and US Forest Service. Data were collected from plots measured for research studies or management projects of varying effort, scale and scope, and across several ecosystems. Most datasets came from large projects using well-established sampling methods, such as the Forest Service Forest Inventory and Analysis (FIA) program, and the LANDFIRE National mapping effort (Rollins *et al*. 2006). The remaining datasets came from smaller projects that often used specialized sampling methods.

Though the data represent a wide variety of ecosystems, we did not attempt to summarize by vegetation type for two reasons. First, as discussed in the introduction, vegetation classifications often do not provide satisfactory descriptions of fuelbeds. Second, the vegetation classifications and descriptions used varied from dataset to dataset. For example, plot data were described by various vegetation descriptions including habitat type, Society of American Foresters cover type (Eyre 1980), Society of

Range Management cover type (Shiflet 1994), Bailey ecoregion (Bailey 1978) or life-form (e.g. 'hardwood'). In several cases, no vegetation description was available.

Extensive preliminary analyses explored the quality of the datasets and sensitivity of FOFEM. This was an iterative process where we compared the size of the dataset, number of inputs the dataset would supply to FOFEM and the effect inputs held constant or set to default would have on the simulation results. The analysis revealed that the following six components provided the optimum description of the fuelbeds in this study: duff, litter, twigs (1-h), branches (10-h), large branches (100-h), and logs. Wildland fire science in the USA defines 1-h fuels as <0.63 cm (<0.25 in) diameter, 10-h fuels as 0.63 to <2.54 cm (0.25 to <1.0 in), and 100-h fuel as 2.54 to <7.62 cm (1.0 to <3.0 in) (Fosberg 1970). In the present study, we defined logs as being 7.62 cm (3.0 in) and greater in diameter, which matches the lower limit of the 1000-h class used in fire modeling. In all cases, the load of down woody material was sampled using planar intersect sampling techniques (Warren and Olsen 1964; Van Wagner 1968; Brown 1971). By using just duff, litter, 1-, 10-, 100-h, and log loads, we were able to maximize the number of useable plots in our master dataset and maintain the usefulness of the FOFEM outputs. When we held a model input constant or set to default, we attempted to quantify the effect it made on model results.

Actual fuelbeds can include other fuel components, such as shrubs, herbaceous plants, and small trees that may substantially influence fire effects, but we did not include these components in the study owing to limited data. This precluded non-forested sites from the study because a relatively small number of plots had a comprehensive and objective assessment of shrub and herbaceous fuelbed load.

We only included data in this study if they were accompanied by a detailed description of the sampling protocols from the associated field handbooks or the principal investigator. Data was not included if attributes were sampled using subjective methods such as ocular estimates or represented conditions on an area greater than 0.1 ha (plot level). We also removed nearly 5000 plots because duff and litter depth were estimated to the nearest 1.3 cm (0.5 in) or were combined in one depth measurement. We felt these two issues reduced the quality of the data enough that the plots should not be included in the study.

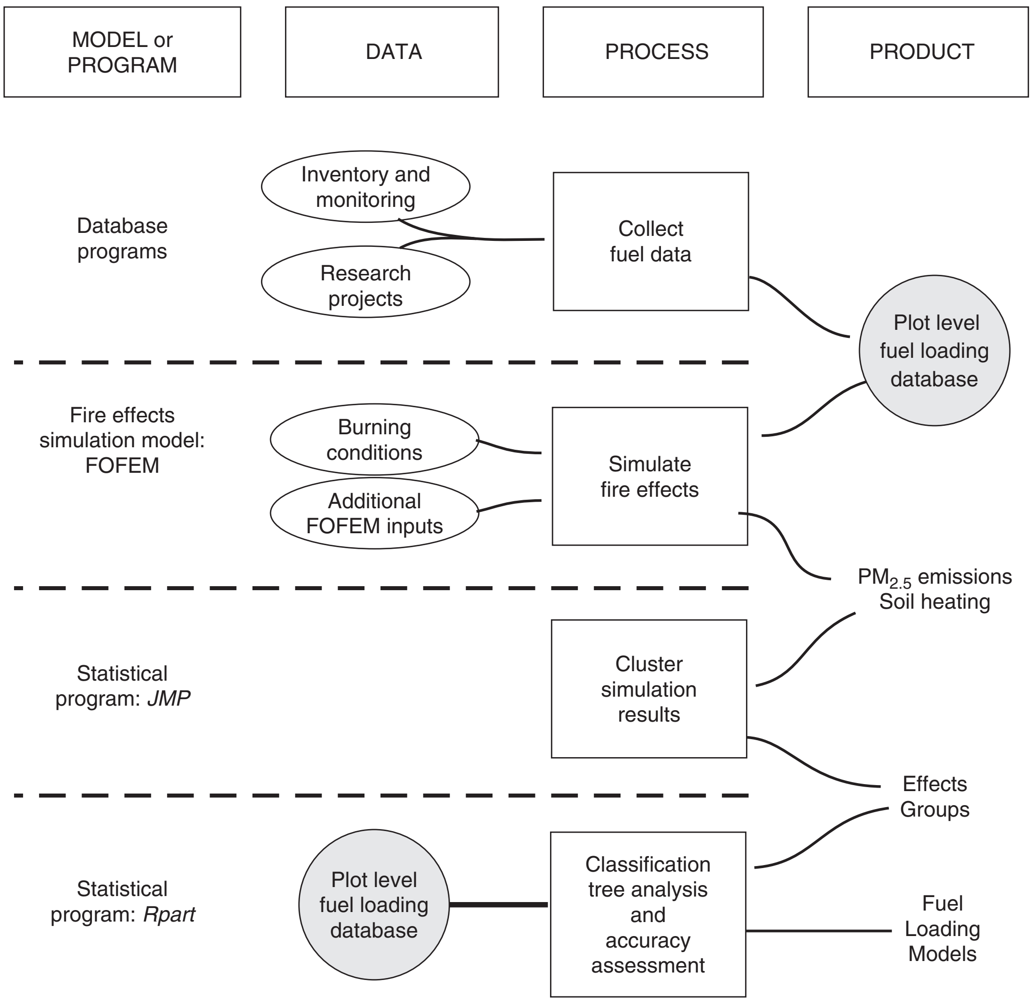


Fig. 1. The general process used to create the Fuel Loading Model (FLM) classification.

Table 1. Description of fuelbed datasets used in the Fuel Loading Models classification

Dataset name	Description	Conifer	Broadleaf	Mixed	Unknown	Total
FIA	National fuels data collected by the US Forest Service, Forest Inventory and Analysis program. Dataset from 2001 (vegetation information included for 247 plots)	89	128	30	819	1066
GMRS	Dataset used in the Gradient Modeling Research Study. Data collected in Montana and Idaho	921	0	0	0	921
SCA-LF	Inventory data collected by the Student Conservation Association in the south-western USA for the Landfire project (life-form information not included with the data)	0	0	0	764	764
Ft Drum	Inventory data collected by the USA Department of the Army at Ft Drum, New York	160	223	163	0	546
SCA-OR	Data collected by the Student Conservation Association for the USA Bureau of Land Management in southern Oregon	87	34	133	0	254
PIAL	Dataset from the whitebark pine research project. Collected in Montana	216	0	0	0	216
FCCS	Dataset including only forested sites in the contiguous USA from a 2004 version of the Fuel Characteristic Classification System	71	16	13	0	100
Baker	Dataset of pre- and post-burn fuels in consumption and emissions studies primarily collected in the south-east USA	6	6	32	48	92
GNP	Data collected in Glacier National Park, Montana	87	0	0	0	87
All	Totals	1637	407	371	1631	4046

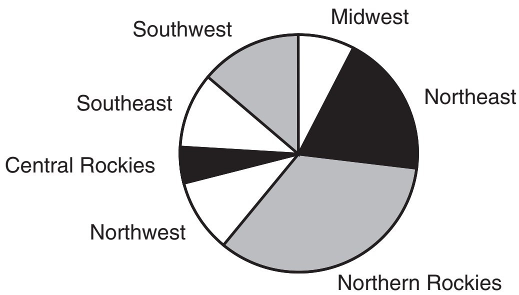


Fig. 2. The geographic distribution of the surface fuel data used to develop the Fuel Loading Models (FLMs) by general United States region.

Table 2. Plot count by state in the Fuel Loading Models dataset

State	Count	State	Count
Alabama	42	Nebraska	4
Arizona	308	Nevada	93
Arkansas	36	New Jersey	9
California	175	New Mexico	51
Colorado	119	New York	580
Florida	32	North Carolina	34
Georgia	53	North Dakota	23
Idaho	683	Oklahoma	32
Illinois	14	Oregon	258
Indiana	13	Pennsylvania	144
Iowa	8	South Carolina	78
Kansas	9	South Dakota	6
Kentucky	24	Tennessee	33
Louisiana	14	Texas	19
Maine	46	Utah	49
Minnesota	97	Virginia	32
Mississippi	46	Washington	50
Missouri	41	Wisconsin	39
Montana	685	Unknown	67

Approximately 90% of the duff and litter load estimates in our study dataset were calculated by averaging multiple depth measurements and then multiplying by a predetermined duff bulk density. The bulk density estimates were either provided with the dataset or we determined them from published literature. Remaining duff and litter load assessments were determined from actual dry weight of samples collected in the field.

Of the ~11 000 plots gathered from across the contiguous USA, the results of this study were based on 4046 plots from forested sites. Though it was not a random sample, the dataset included fuels data from across of the USA (Fig. 2). Dataset name, brief description, plot count by general life-form and sample size are presented in Table 1. Plot count by state is presented in Table 2.

Simulating fire effects

Fire effects were simulated for each plot using the FOFEM fire effects model (Reinhardt *et al.* 1997; Reinhardt and Keane 1998; Reinhardt 2003). We selected FOFEM because: (1) it is a scientifically documented and well-established fire effects model; (2) it uses plot-scale data that are readily available; (3) it uses BURNUP, which is a physics-based mechanistic consumption model that is not constrained by empirical relationships (Albini *et al.* 1995; Albini and Reinhardt 1997); (4) it was designed for use across the contiguous United States (the scope of the present study); and (5) it is unique among fire effects models in that it simulates soil heating and emissions. Although many fire effects models could have been used for the type of classification presented in this study, we used FOFEM because it fulfilled our design requirements.

We selected $PM_{2.5}$ emissions ($Mg\ km^{-2}$) and maximum soil surface temperature (°C) as the FOFEM clustering variables to represent fire effects. Managers also suggested including tree mortality as an important fire effect but we did not use tree mortality in the FLM classification because: (1) tree mortality is highly dependent on the size and species of tree and none of the fuels plots had the associated tree data needed to compute mortality, and (2) mortality is correlated with crown scorch but FOFEM does not simulate flame height or flame length, so crown scorch could not readily be estimated.

Fuel loadings by component are the primary input requirements for FOFEM (Reinhardt *et al*. 1997). However, there were some FOFEM fuel inputs that we could not quantify from the collected plot data, such as shrub and herbaceous loadings and log size class distribution. In the absence of a specific user input, FOFEM uses default values compiled from an extensive analysis of field data and the literature (Mincemoyer 2002). When our dataset did not include a FOFEM input we either used the FOFEM default or held the input constant based on an analysis of the study dataset.

Many of the plots in our dataset were missing herbaceous or shrub load so we used the median values of the 1339 plots that had herb and shrub loading information: $0.05\ kg\ m^{-2}$ and $0.08\ kg\ m^{-2}$ respectively. The influence of this assumption on the study results is unknown.

In addition to the fuelbed component loadings, the BURNUP model embedded in FOFEM (Albini *et al*. 1995; Albini and Reinhardt 1997) requires an estimate of rotten log load and log load distribution in diameter classes. In the current study, rotten log load was unknown for 1615 of the plots. We tried to estimate percentage rot from the plot data using regression techniques but found no significant relationship between total down woody debris load or total log load and the percentage of rotten log load. We examined the percentage rotten of total log load on the 1763 plots where rot was sampled and found a highly bimodal distribution. The percentage of rotten log load was 100% on 446 plots, 0% on 214 plots, and averaged 53% on the remaining 1083 plots. We used the 53% value for the 1615 plots where it was unknown. We also tested the sensitivity of this parameter by simulating the plots where the percentage of rotten log load was known under two rot scenarios in FOFEM: (1) sampled percentage rotten value, and (2) the 53% mean. When total $PM_{2.5}$ emissions and maximum soil surface temperature were clustered, substituting average 53% rot resulted in a shift of 8–10% of the plots being clustered differently than when using the known value. There was no directional bias in the emissions or soil temperature when the average 53% rot was used.

Log load distribution across log diameter classes is passed to BURNUP to improve the precision of simulated burning rate and the total log load consumption. FOFEM uses five generic representations of log load distribution across log diameter classes:

(1) Left – most of the load is in pieces 7.6 to 22.9 cm (3 to 9 in) in diameter;
(2) Right – most of the load is in pieces 22.9 cm (9 in) and larger in diameter;
(3) Center – load is concentrated in the 15.2 to 50.8 cm (6 to 20 in) diameter range;
(4) End – load is in pieces 7.6 to 15.2 cm (3 to 6 in) and >50.8 cm (20 in) in diameter;
(5) Even – the load in all diameter classes is within 10% of others.

Only 226 plots in our development dataset had sufficient log diameter information to derive a diameter distribution. We simulated each of those plots using all five log diameter distributions and found no significant difference in total $PM_{2.5}$ emissions or maximum soil surface temperature. This was not an intuitive result and likely owing to the small sample size and high variability in log load. We assigned all plots the left distribution class because 61% of the 226 plots had this distribution.

Several other FOFEM inputs are important for simulating emissions and soil temperature but unrelated to the measured plot loadings. We used the 'dry' FOFEM fuel moisture regime for all simulations. With this regime, the moisture content for 10-h (branches) fuels was set at 10%, logs at 15%, duff at 40%, and soil at 10%. We also specified that each simulation was characterized as a wildfire condition by setting the season of burn to 'summer'. We set all fuels as 'natural' and soil type to 'coarse-silt'. Fuel source and soil type do not influence simulation of emissions or soil surface temperature in FOFEM.

Clustering fire effects simulation results

We simulated $PM_{2.5}$ emissions and maximum soil surface temperature for all 4046 plots in FOFEM, then clustered the standardized emissions into 10 groups using Ward's hierarchical method – an agglomerative hierarchical cluster analysis commonly used to form clusters of objects (JMP IN 2003). In agglomerative hierarchical clustering, each object (i.e. plot) begins in a separate cluster and objects are successively combined into clusters until all objects form one cluster. At each step, individual objects are added to clusters or clusters are merged. This approach calculates the mean of all variables for each cluster, then calculates the Euclidean distance between each object and all cluster means and, finally, the distances are then summed for all objects. At each step, clusters are merged in a way that minimizes the increase in the overall sum of the squared within-cluster distances.

We called the 10 clusters 'Effects Groups' and used Tukey Honestly Significant Difference tests to confirm statistical differences in total $PM_{2.5}$ emissions and maximum soil surface temperature across the Effects Groups. Only 10 clusters were specified because we found, through several exploratory analyses, that the FLM classification rules (discussed below) were unable to uniquely identify differences between some clusters when more than 10 clusters were used. We could have clustered into fewer than 10 groups, but we wanted the maximum number possible to maintain precision and resolution of the Effects Groups. We used the *JMP* statistics package for all clustering and testing statistical analyses and used a 95% confidence level throughout (JMP IN 2003).

Classifying forest fuels data to build FLMs

Classification tree analysis was used to build a rule set for predicting the Effects Groups from component fuel loading. We used the library section *Rpart* (Therneau and Atkinson 1997) in the *R* statistical software package (R-Project 2005) because it creates a classification tree and simultaneously computes the optimal pruning for that tree (Venables and Ripley 2002). The classification tree analysis in *Rpart* can determine the unique relationships between continuous loading variables (e.g. the fuelbed components) and the categorical dependent variable (e.g. Effects Group). *Rpart* includes 10-fold cross-validation, which has been found to provide satisfactory estimates of true misclassification error in most simulations (Breiman *et al.* 1984).

The endpoint of a classification tree consists of nodes that partition the dataset into distinct classes or categories. In the present study, each node was described by some combination of duff, litter, FWD, and log load (exploratory analyses noted that 1-, 10-, and 100-h components were not significant classification predictors when used individually, so the components were summed to form the FWD fuelbed component). *Rpart* also calculated the proportion of plots assigned to each Effects Group at each node. For example, in one case, 79% of the plots with component fuel loading within the ranges at one node were classified in the correct Effects Groups whereas the other 21% of the plots were misclassified into other Effects Groups. The *Rpart* proportions were used to calculate node impurity, the 10-fold misclassification and observed *v.* predicted Effects Groups in the contingency tables. Each of these is described in subsequent parts of the paper.

The recursive partitioning methods used to develop the FLMs optimize each split in the classification tree without optimizing the entire tree at once by defining a measure of impurity (i.e. the ability of the classification rules to predict an Effects Group) at each node and choosing a split that reduced the average impurity over all nodes (Venables and Ripley 2002). The Gini index (Venables and Ripley 2002) was used to measure node impurity. It reaches a value of zero when only one class is present at a node and reaches its maximum value when class sizes at the node are equal. All prior probabilities were set equal for each class rather than the frequency of occurrence in our datasets because we were not certain our dataset was a representative sample of fuelbeds. Once partitioning rules were developed, we specified that the resultant tree would have at least one node for each of the Effects Groups. The classification tree analysis revealed there could be multiple nodes leading to one Effects Group, with each node identified by a unique range of duff, litter, FWD, and log load.

The last step was to assign each FLM representative loading values for duff, litter, 1-, 10-, 100-h, and log components so the FLM classes could readily be used in fire models. Representative load was the median fuel loading of each component for the plots assigned to the FLM. Median load of duff, litter, and log components came directly from the plot data. Because 1-, 10-, and 100-h fuel loadings had been combined in the classification procedure, the median loads of these components were assigned by multiplying median FWD load (determined in the classification procedure) by the median proportion of total FWD load made up by 1-, 10-, and 100-h loading respectively for each FLM.

Assessing accuracy of FLM classification

We evaluated the ability of the FLM rule set to predict the correct Effects Group in two ways. First, we used the default, *Rpart* 10-fold cross-validation routine (Venables and Ripley 2002) where the dataset was randomly split into 10 approximately equal parts with nine parts used to build the tree and the tenth part used to test the tree. This process was repeated 10 times and results were averaged for each set of FLMs. Second, we compared predicted *v.* observed Effects Groups using contingency tables. The *Rpart* classification procedure calculates the probability that each Effects Group will be assigned to each of the nodes. We used these probabilities to calculate the number of plots assigned to each Effects Group for each node. Using the contingency analysis, we then calculated misclassification rates and bias of Effects Groups at two levels of precision: (1) when the predicted Effect Group was not the same as the observed Effects Group, and (2) when the predicted Effects Group was not the same as the observed Effects Group or one of the adjacent Effects Groups. We defined adjacent Effects Groups as the Effects Groups immediately around the Effects Group of interest, in two-dimensional space.

Results

Effects Group clusters

The clustered FOFEM $PM_{2.5}$ emissions and maximum surface soil temperature predictions for each plot in the dataset are shown in Fig. 3 as 10 distinct Effects Group (EG in Fig. 3). The 10th and 90th percentile of emissions and maximum soil surface temperature that bound each Effects Group are presented in Table 3 to illustrate the differences in fire effects. We found that most fuelbeds in our plot database produced low emissions and created only moderate soil surface heating under our simulated moisture conditions. This resulted in the majority of Effects Groups being created in a small range of emissions and soil temperature values. No plots created high emissions and high soil temperature because of the insulating properties of non-smoldering duff (Hartford and Frandsen 1992; Valette *et al.* 1994).

FLM classification

The *RPart* classification process resulted in the creation of 21 distinct FLM classes. The 1-, 10-, 100-h fuel loadings were not significant variables for predicting FLMs when used separately, but when summed to create the FWD component, they had significant predictive value. *Rpart* results also indicated that log load was a significant factor for determining the FLM classes and that keeping duff and litter load separate decreased the cross-validation error of the FLMs by ~9%.

The FLM decision criteria key (i.e. rule set) is shown in Table 4. An FLM is identified when the loadings of each of the four components falls between the upper and lower boundary for the class. The first two digits following the 'FLM' represent the Effects Group (numbered 01 to 10) and the last digit represents the sequential FLM number. FLM102, for example, describes the second set of fuels that lead to the emissions and soil temperature seen in EG10. We converted Table 4 to a dichotomous FLM field key that is presented in Sikkink *et al.* (2009) along with detailed sampling instructions. Median fuelbed component loads for each FLM are presented in Table 5. These values are designed to be used as input to FOFEM or other plot-level fire effects models.

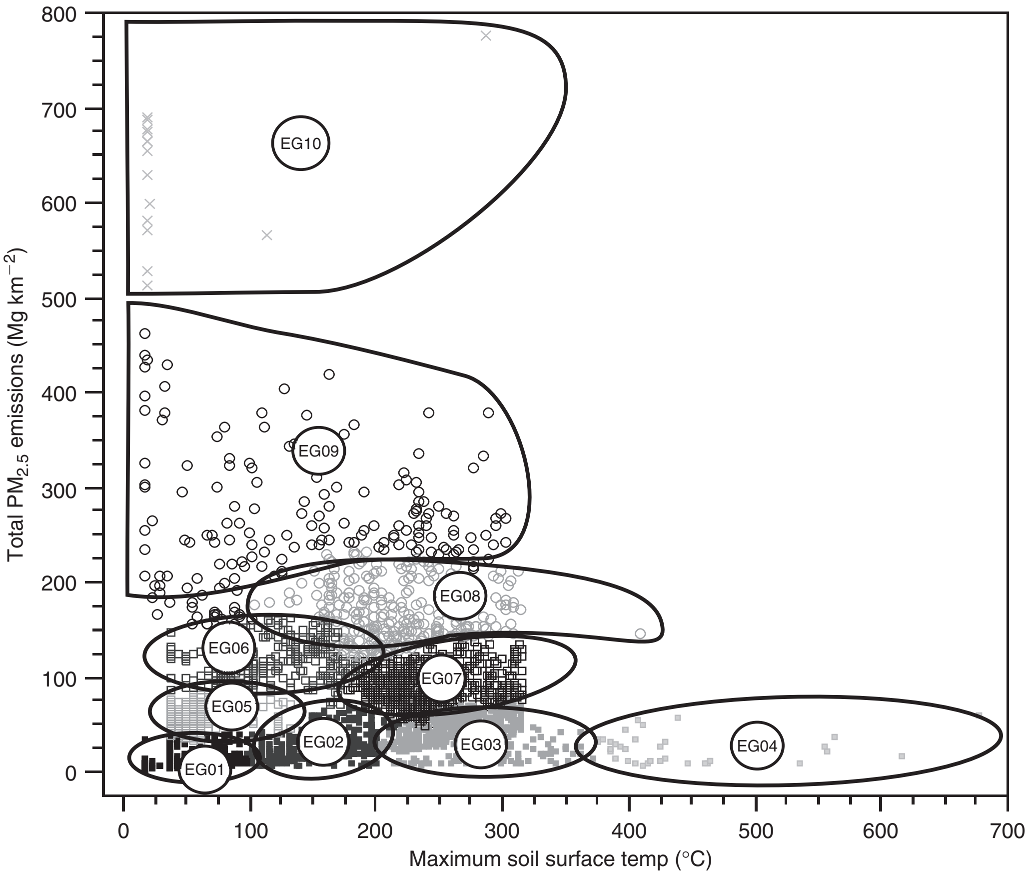


Fig. 3. The location of the 10 Effects Groups derived from the clustering procedure in fire effects space (emissions and soil heating). The groups are outlined so they can be identified more easily.

Table 3. Range of $PM_{2.5}$ (particulate matter <2.5 μm in diameter) emissions and maximum soil surface temperature for each Effects Group
Unit conversions for Total $PM_{2.5}$ emissions is tons acre^{-1} = 4.46 Mg km^{-2}; for maximum soil surface temperature is °F = 1.8 × (°C + 32°)

Effects Group	*n*	Total $PM_{2.5}$ emissions (Mg km^{-2})		Maximum soil surface temperature (°C)	
		10th percentile	90th percentile	10th percentile	90th percentile
EG01	1327	0.22	18.75	19	68
EG02	431	9.46	45.89	117	196
EG03	605	18.81	61.40	225	310
EG04	36	6.11	48.25	386	561
EG05	272	39.11	76.52	38	86
EG06	303	87.49	142.97	73	169
EG07	600	65.03	114.99	201	297
EG08	282	130.84	210.85	167	279
EG09	174	175.57	364.32	30	266
EG10	16	520.44	713.13	19	165

FLM classification error

We found the 10-fold misclassification cross-validation error was 0.34. Contingency tests revealed that most Effects Groups were identified by the FLM rule set with better than the 34% cross-validation error rate (Table 6). The exceptions were EG03 and EG05, which were misclassified 48 and 38% of the time respectively. Average misclassification rate calculated using the probabilities provided by the *Rpart* classification was 31%. This improved to 15% misclassification when adjacent Effects Groups were combined (Table 7).

Discussion

Our primary objective was to develop a procedure for classifying fuels based on fuelbed characteristics and not the overlying

Table 4. The Fuel Loading Model (FLM) rule set

An FLM is selected when the load of all four components falls within the specified range. FWD is total fine woody debris loading (sum of 1-, 10-, and 100-h). The Effects Group is identified in the leftmost column (numbered 01 to 10) by the first two digits following FLM. The last digit is the sequential FLM number. Values in bold text are from the classification procedure. Non-bold values indicate limits of the data. Unit conversion for loadings is tons $\text{acre}^{-1} = 4.46\,\text{kg}\,\text{m}^{-2}$

FLM	Loading ($\text{kg}\,\text{m}^{-2}$)							
	Duff		Litter		FWD		Log	
	Lower (≥)	Upper (<)	Lower (≥)	Upper (<)	Lower (≥)	Upper (<)	Lower (≥)	Upper (<)
FLM011	0.00	**0.42**	0.00	31.04	0.00	**0.53**	0.00	47.23
FLM012	0.00	**0.42**	0.00	**0.21**	**0.53**	14.34	0.00	47.23
FLM013	**0.01**	**0.42**	**0.21**	31.04	**0.53**	14.34	0.00	47.23
FLM021	**0.42**	**1.12**	0.00	31.04	0.00	14.34	0.00	**2.27**
FLM031	**1.12**	**2.99**	0.00	**2.43**	0.00	14.34	0.00	**1.83**
FLM041	0.00	**0.01**	**0.21**	31.04	**0.53**	14.34	0.00	47.23
FLM051	**2.99**	**4.23**	0.00	**0.61**	0.00	14.34	0.00	**1.00**
FLM061	**0.42**	**1.12**	0.00	31.04	0.00	14.34	**2.27**	**6.35**
FLM062	**4.23**	**4.87**	0.00	**0.61**	0.00	14.34	0.00	**1.00**
FLM063	**2.99**	**4.87**	0.00	**0.61**	0.00	14.34	**1.00**	**3.57**
FLM064	**4.87**	**8.45**	0.00	31.04	0.00	14.34	0.00	**3.57**
FLM071	**1.12**	**2.99**	0.00	31.04	0.00	14.34	**1.83**	**3.57**
FLM072	**2.99**	**4.87**	**0.61**	31.04	0.00	14.34	0.00	**2.29**
FLM081	**0.42**	**1.12**	0.00	31.04	0.00	14.34	**6.35**	47.23
FLM082	**2.99**	**4.87**	**0.61**	31.04	0.00	14.34	**2.29**	**3.57**
FLM083	**1.12**	**5.90**	0.00	31.04	0.00	14.34	**3.57**	**7.88**
FLM091	**8.45**	**13.41**	0.00	31.04	0.00	14.34	0.00	**3.57**
FLM092	**1.12**	**13.41**	0.00	31.04	0.00	14.34	**7.88**	47.23
FLM093	**5.90**	**13.41**	0.00	31.04	0.00	14.34	**3.57**	**7.88**
FLM101	**13.41**	80.00	0.00	31.04	0.00	14.34	0.00	47.23
FLM102	**1.12**	**2.99**	**2.43**	31.04	0.00	14.34	0.00	**1.83**

Table 5. The median loadings by fuel component assigned to each Fuel Loading Model (FLM) for use in fire effects models

Median litter, duff, and log fuel load was determined from the data in each FLM class. Derivation of the median 1-, 10-, and 100-h loading is described in the text. Unit conversion for loadings is tons $\text{acre}^{-1} = 4.46\,\text{kg}\,\text{m}^{-2}$

FLM	*n*	Loadings ($\text{kg}\,\text{m}^{-2}$)					
		Duff	Litter	Twigs (1-h)	Branches (10-h)	Large branches (100-h)	Logs (1000-h)
FLM011	1223	0.00	0.04	0.01	0.02	0.01	0.00
FLM012	52	0.00	0.06	0.06	0.35	0.60	0.58
FLM013	54	0.27	0.56	0.05	0.34	0.46	0.50
FLM021	497	0.74	0.26	0.04	0.14	0.15	0.21
FLM031	766	1.64	0.42	0.06	0.20	0.24	0.34
FLM041	61	0.00	0.54	0.06	0.37	0.58	0.58
FLM051	80	3.55	0.34	0.04	0.25	0.32	0.32
FLM061	57	0.81	0.20	0.06	0.29	0.55	3.75
FLM062	28	4.61	0.30	0.03	0.21	0.28	0.36
FLM063	50	3.82	0.34	0.04	0.31	0.53	1.74
FLM064	203	5.80	0.65	0.07	0.25	0.37	0.75
FLM071	182	2.10	0.49	0.10	0.32	0.49	2.58
FLM072	271	3.76	0.85	0.09	0.23	0.30	0.64
FLM081	25	0.89	0.20	0.07	0.26	0.60	8.15
FLM082	47	3.97	0.85	0.12	0.35	0.71	2.70
FLM083	237	2.67	0.56	0.11	0.36	0.64	5.03
FLM091	52	10.30	0.26	0.07	0.32	0.37	0.65
FLM092	97	3.33	0.68	0.12	0.36	0.74	10.34
FLM093	33	7.36	1.39	0.13	0.31	0.54	4.82
FLM101	24	22.42	2.24	0.09	0.21	0.24	0.36
FLM102	7	2.35	4.03	0.03	0.11	0.24	1.03

Table 6. Contingency table comparing observed *v.* predicted Effects Groups (EG)
Numbers in italics indicate perfect agreement

		Predicted Effects Groups										Plots	Number misclassified	Percentage misclassified
		EG01	EG02	EG03	EG04	EG05	EG06	EG07	EG08	EG09	EG10			
Observed Effects Groups	EG01	*924*	79	98	95	72	29	0	4	26	0	1327	403	30.4
	EG02	31	*344*	2	0	48	5	2	0	0	0	431	87	20.2
	EG03	9	24	*313*	0	211	2	46	0	0	0	605	292	48.3
	EG04	0	0	2	*34*	0	0	0	0	0	0	36	2	5.6
	EG05	0	7	3	0	*168*	47	47	0	0	0	272	104	38.3
	EG06	0	5	0	0	13	*225*	21	34	4	0	303	78	25.7
	EG07	0	7	28	0	52	48	*429*	29	8	0	600	171	28.5
	EG08	0	0	0	0	1	15	40	*191*	35	0	282	91	32.3
	EG09	0	0	0	0	0	1	0	31	*132*	11	174	42	24.1
	EG10	0	0	0	0	0	0	0	1	1	*14*	16	2	12.5
	Total											4046	1272	31.4

Table 7. Misclassification rate when the observed Effects Group (EG) was not the same as the predicted EG and not the same as one of the EGs adjacent to the predicted EGs
Adjacent EGs are those immediately surrounding the EG of interest in two-dimensional space

Observed Effects Group	Predicted and adjacent Effects Groups	Number misclassified	Percentage misclassified
EG01	EG01, EG02, EG05	253	19.0
EG02	EG01, EG02, EG03, EG05, EG07	5	1.2
EG03	EG02, EG03, EG04, EG07	222	36.7
EG04	EG03, EG04	0	0.0
EG05	EG01, EG02, EG05, EG06	50	18.5
EG06	EG05, EG06, EG07, EG08, EG09	5	1.7
EG07	EG02, EG03, EG06, EG07, EG08	60	9.9
EG08	EG06, EG07, EG08, EG09	1	0.3
EG09	EG06, EG08, EG09	11	6.0
EG10	EG10	2	9.4
Total		608	15.0

vegetation. With a cross-validation error rate of 34%, it might appear that our approach for estimating emissions and soil temperature was insensitive to changes in fuel load, but two results indicate that it worked better than the misclassification error suggests. First, 52% of the misclassified plots were predicted to be in an Effects Group adjacent to the observed Effect Group, implying the simulated effects were similar even when the Effects Group was not predicted correctly. Second, 6 of 10 Effects Groups were reached by more than one FLM in our classification key. Judging from these two observations, we found that FOFEM was sensitive enough to simulate the change in fire effects caused by subtle changes in duff, litter, 1-, 10-, 100-h, and log load within a fuelbed. To illustrate, compare FLM061 and FLM062 in Tables 4 and 5. Both FLMs lead to Effects Group 06 and the total fuel load for each FLM is approximately the same; however, FLM061 is reached by relatively low duff and high log load while FLM062 is reached with relatively high duff and low log load. So, although these two FLMs lead to the same Effects Group (emissions and soil temperature), they have significantly different fuel attributes. The low number of FLMs in this classification is primarily owing to the difficulty in predicting emissions and soil temperature from fuelbeds with highly variable fuel loads. The somewhat promising results of this study indicate our methods may work well for classifying fuels using different fuelbed components, fire effects, and fire effects simulation models than were used in this study, without the need to incorporate a vegetation-based system.

Our secondary objective was to design a fuels classification that incorporated fire effects at regional or larger scale. We feel the Effects Groups reflect that broad scale by separating significantly different fire effects for disparate fuelbeds. The high variability of fuel load across fuel components dictates the reliability of any fuel classification. The design of the FLM classification balances the high variability of sampled surface fuels with the resolution at which we can predict fire effects (i.e. FOFEM) and maximizes our ability to discriminate between dissimilar fuelbed complexes.

Total $PM_{2.5}$ emissions and maximum soil surface temperature as simulated from FOFEM tended be poorly correlated when duff was present. Duff combustion often provides a substantial proportion of the total emissions produced during a wildfire (Sandberg 1980), but it also can function as an insulator, protecting the soil surface from radiated heat (Hartford and Frandsen 1992; Valette *et al*. 1994). The combustion of surface fuels can also affect soil surface temperature under certain conditions (DeBano *et al*. 2005). If the entire duff layer is consumed or if the duration of the burn is long (including independent burning of the duff layer), soil surface temperature can be substantially higher than when a residual duff layer is present. Sandberg (1980) reported that duff begins to burn independently when gravimetric duff moisture is lower than 30%. We used the 'dry' moisture regime in FOFEM, which sets the duff moisture at 40%; thus this study does not include the soil surface heating or emissions influences of independently burning duff. Though subsurface heating may have been a more useful fire effect to study, we selected temperature at the soil surface to eliminate the need to model the complex interaction between subsurface soil heating and soil type (texture), soil moisture and mineral content. These three soil properties strongly influence the magnitude and duration of the subsurface heat pulse (Frandsen 1987; DeBano *et al*. 2005), but were not quantified in any of the more than 11 000 plot data records originally collected for the study. Emissions, however, are highly dependent on the consumption of ground and surface fuels – if high levels of biomass are consumed, then, in general, there are corresponding high levels of emissions (Fahnestock and Agee 1983; Ottmar *et al*. 1996; Taylor and Sherman 1996; Sandberg *et al*. 2002). Other fire effects, such as tree morality, were not included in this classification because factors unrelated to duff, litter, FWD, and log loading would influence mortality, such as tree size, bark thickness, and growth-habit (Ryan and Reinhardt 1988).

Study limitations

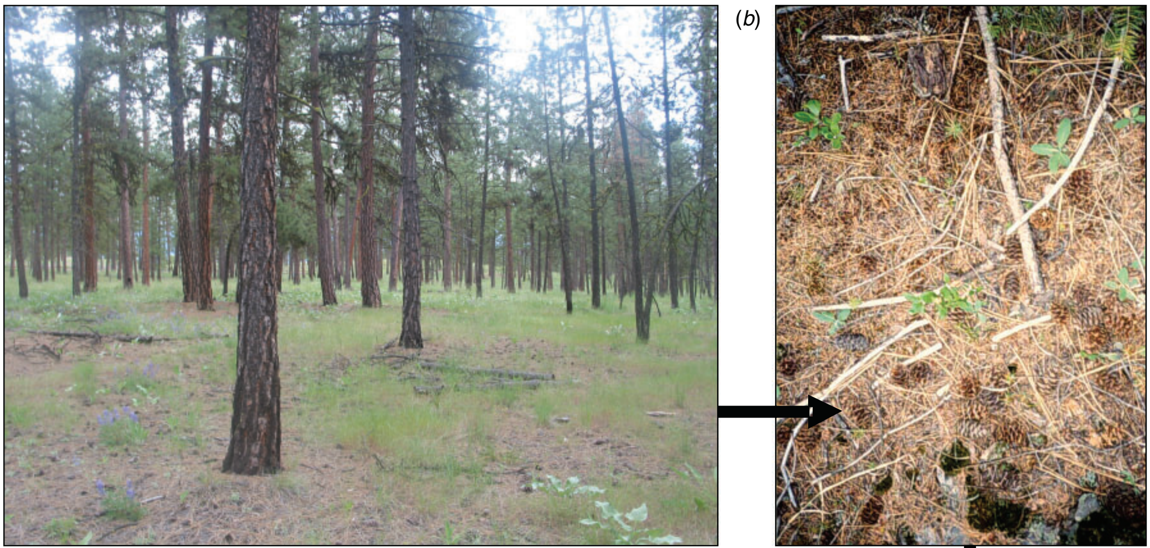
There are several limitations of this Fuel Loading Model classification that may influence its use. First, even though plots were gathered from many sources and included more than 4000 plots, the data may not fully represent the entire range of fuelbed conditions found across the contiguous United States. Some rare fuel complexes in ecologically restricted ecosystems, such as pocosin swamps, alpine tundra, and redwood forests, were missing in our datasets. Ecosystems rarely sampled for fuels, such as deserts and marshes, were also absent in our analysis. Limitation in the availability of electronic data led to a non-random sample (clumped distribution) of fuelbeds, nationally. For example, 48% of the plot records used in the FLM classification were collected in Montana, Idaho, and New York. The bias in study results owing to the limited data is unknown. If the current FLM classification is shown to be useful in land management, we suggest that a more intensive study be undertaken sometime in the future. This study should conduct an extensive data search, collect fuels data across as many regions and ecosystems as possible and use the most up-to-date fire effects simulation model to create a more comprehensive classification.

Data for crown fuels was almost non-existent in the datasets we gathered, so we made no attempt to include emissions or soil heating produced by crown fire or develop FLM classes using crown loading. Likewise, few plots included enough information to estimate emissions and soil heating for non-forested sites. Less than 200 plots (of the over 11 000 plots assembled for this study) included fuel loading data for the herbaceous and shrub components measured using clip and weigh sampling, and also included duff and litter assessments. Given the small sample size, we made no attempt to include variable loading of herbaceous and shrub fuels in this classification, instead holding them constant at 0.05 and 0.08 kg m^{-2} respectively in each of the 4046 fuelbeds in the study. Because the consumption of herbaceous and shrub components may contribute a substantial part of the total emissions and soil heating effects in rangeland systems, the absence of variable herb and shrub load data in this study may mean the FLMs do not represent fire effects in rangeland systems. The same issue may also be present on forested sites where the biomass of the herbaceous and shrub understorey is a substantial part of the total ground and surface fuel component. Fuel consumption of tree crowns and shrublands is not well understood (Sandberg *et al*. 2002), so we cannot gauge how different the FLM classification would have been if these components had been included as variables in the study.

The FLM classification contains a decision key that objectively and repeatably identifies unique fuel classes from measurements of fuel properties on the ground or from previously collected field data. Depending on the loading and spatial distribution of the down woody material, it may require numerous transects to sample fuels at the precision necessary for the FLM key when using the planar intersect technique. Also, the decision criteria used to differentiate FLM013 and FLM041 required duff depth be measured to 0.01 cm – a precision that cannot be measured in the field.

Our FOFEM simulation results may have over generalized actual fire effects seen at the plot level because the imbedded models in FOFEM, specifically BURNUP (Albini *et al*. 1995) and the soil heating model (Campbell *et al*. 1995), oversimplify the simulation of fire effects to manage model logic and to reflect our imperfect understanding of the relationships important for predicting effects. For example, the soil heating model in FOFEM has two variants: one that simulates soil heating when duff is present and one that simulates the no-duff situation. However, FOFEM does not predict duff consumption rate, so the model cannot simulate the change in soil heating when the duff layer is consumed during flaming or smoldering combustion. Thus, only sites with very little duff show the highest soil temperature in this study. If FOFEM were able to switch between the duff and no-duff soil heating models mid-simulation, then high soil-surface temperatures would likely have been noted in fuelbeds with the greater duff depth than seen in FLM041. The simulation results were further generalized by incomplete attribute information, such as diameter distribution of logs, within the plot data we used as inputs. Additional attribute information and a larger sample size would likely have led to more Effects Groups and FLM classes. We also recognize some FOFEM values held constant in this study (e.g. percentage rotten log load, and shrub and herb load) may not be typical for many sites.

We used the 'dry' moisture regime and 'summer' season settings in FOFEM to represent wildfire burning conditions in the western USA. Fuel moistures in the eastern USA, especially in the south-east, are higher when conditions are 'dry' than used in our simulations. Also, most major wildfires in the south-eastern (*a*) (*b*)



(*c*)

FLM key

If a forest type

If $1.12 \geqslant$ duff > 2.99 kg m^{-2} and
logs < 1.83 kg m^{-2} and
litter < 2.43 kg m^{-2} then
FLM = 031

(*d*)

Fuel component	Observed loadings (kg m^{-2})	Keyed FLM031 loadings (kg m^{-2})
Litter	0.56	0.42
Duff	2.04	1.64
1-h	0.01	0.06
10-h	0.17	0.20
100-h	0.05	0.24
1000-h	1.13	0.34
$PM_{2.5}$ (Mg ha^{-1})	39.40	33.60
Surface temp (°C)	256.00	256.00

Fig. 4. An example of the identification of Fuel Loading Models (FLMs) in the field. (*a*) A person would walk into an area, and (*b*) assess the fuels, and (*c*) use Table 4 to identify the FLM. (*d*) Median loadings of FLM031 (Table 5) are compared against the measured values of this stand to illustrate the accuracy of FLMs for estimating loadings.

USA occur in the spring before vegetation green-up and in the fall after the first frost. Thus, the FLM classification may not be appropriate for use in the south-eastern USA.

Management applications

Detailed instructions on the use of the FLM classification are contained in the field guide of Sikkink *et al.* (2009), which includes field sheets, photo guides, and a streamlined, easy-to-use key. In short, a person would walk into a stand or plot and compare observed fuel loadings with the key criteria (Table 4) to identify a unique FLM class. This person need only determine if the loadings of the four components are above or below threshold values. Duff and litter depth are measured, converted to loading and keyed. Woody material is assessed by comparing plot conditions with a set of photographs that represent the critical key values (Fig. 4). These photos were developed from techniques used to estimate fuel loadings using the Photoload technique (Keane and Dickinson 2007). It often takes less than 10 min for field personnel to identify an FLM in the field. Once the FLM classes are objectively classified, they can then be: (1) used as a fuel inventory method to describe duff, litter, FWD, and log loadings at any scale; (2) used to estimate the amount of carbon in the fuelbed for carbon budget inventories; and (3) used as inputs to fire effects models, such as FOFEM and CONSUME, to compute smoke emissions, fuel consumption, and carbon released to the atmosphere. In spatial analysis applications, FLMs can be mapped across large regions using statistical modeling approaches where FLM classes are correlated with biophysical variables, such as precipitation, evapotranspiration, and site index (Keane *et al.* 2006). Because FLM classes can be objectively identified in the field using a key, field assessments can be used to validate and then refine mapped FLMs. If wildfires occur, the FLM maps can be updated by post-fire sampling or by simulating fuelbed changes in fire effects models, then rekeying the burned fuelbed to a new FLM.

Summary

This study presents a possible method for developing a fuels-based fuel loading classification and presents a generalized classification of fuelbeds (FLMs) that may be used at multiple scales. It is the first such study to actually classify fuels into statistically unique categories using fuel loading data based on simulated fire effects (total $PM_{2.5}$ emissions and maximum soil surface temperature) as classification variables so that the resultant classification recognizes unique fire effects. The FLM classification is not meant to be the definitive national fuels classification owing to the lack of quality fuels data across all ecosystems of the USA, but we feel it is the best currently available. If interest warrants, others should develop a better classification as additional fuel data become available in the future. Even with the limited fuel data, we feel FLMs will be useful for describing natural fuelbeds at large regional scales for the purposes of sampling, mapping, modeling, and predicting fire effects.

The classification process described in this paper, including methods to determine the precision of the results, can be used to build new, more comprehensive, and specialized fuel classifications as additional fuels data become available. Although this study used data collected at a national scale, the same methods could be applied at finer resolutions with more localized fuel datasets to create regional classifications that may be more accurate and consistent. Moreover, this classification process can be modified to include any quantifiable fire effects (e.g. tree mortality, fuel consumption, and subsurface soil heating), classification factors (e.g. shrub and herb load, crown fuels), or fire effects simulation models (e.g. CONSUME). Statistical analyses could then be used to easily link local classifications to regional and national efforts.

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References

Albini FA, Reinhardt ED (1997) Improved calibration of a large fuel burnout model. *International Journal of Wildland Fire* **7**, 21–28. doi:10.1071/WF9970021

Albini FA, Brown JK, Reinhardt ED, Ottmar RD (1995) Calibration of a large fuel burnout model. *International Journal of Wildland Fire* **5**, 173–192. doi:10.1071/WF9950173

Anderson HE (1982) Aids to determining fuel models for estimating fire behavior. USDA Forest Service, Intermountain Forest and Range Experiment Station, General Technical Report INT-GTR-122. (Ogden, UT)

Bailey RG (1978) Description of the ecoregions of the United States. USDA Forest Service, Miscellaneous Publication Number 1391. (Washington, DC)

Breiman L, Friedman JH, Olshen RA, Stone CJ (1984) 'Classification and Regression Trees.' (Wadsworth International Group: Belmont, CA)

Brown JK (1971) A planar intersect method for sampling fuel volume and surface area. *Forest Science* **17**, 96–102.

Brown JK, Bevins CD (1986) Surface fuel loadings and predicted fire behavior for vegetation types in the northern Rocky Mountains. USDA Forest Service, Intermountain Forest and Range Experiment Station, Research Note INT-RN-358. (Ogden, UT)

Brown JK, See TE (1981) Downed dead woody fuel and biomass in the northern Rocky Mountains. USDA Forest Service, Intermountain Forest and Range Experiment Station, General Technical Report INT-GTR-117. (Ogden, UT)

Burgan RE, Rothermel RC (1984) BEHAVE: Fire behavior prediction and fuel modeling system – FUEL subsystem. USDA Forest Service, Intermountain Forest and Range Experiment Station, General Technical Report INT-GTR-167. (Ogden, UT)

Busse MD, DeBano LF (2005) Soil biology. In 'Fire Effects on Soil and Water'. (Eds DG Neary, KC Ryan, LF DeBano) USDA Forest Service, Rocky Mountain Research Station, General Technical Report RMRS-GTR-42, Vol. 4, Ch. 4, pp. 73–91. (Ogden, UT)

Campbell GS, Jungbauer JD, Bidlake WR, Hungerford RD (1995) Soil temperature and water content beneath a surface fire. *Soil Science* **159**, 363–374. doi:10.1097/00010694-199506000-00001

DeBano LF, Neary DG, Ffolliott PF (2005) Effects on soil physical properties. In 'Fire Effects on Soil and Water'. (Eds DG Neary, KC Ryan, LF DeBano) USDA Forest Service, Rocky Mountain Research Station, General Technical Report RMRS-GTR-42, Vol. 4, Ch. 2, pp. 29–51. (Ogden, UT)

Eyre FH (Ed.) (1980) 'Forest Cover Types of the United States and Canada.' (Society of American Foresters: Washington, DC)

Fahnestock GR, Agee JK (1983) Biomass consumption and smoke production by prehistoric and modern forest fires in western Washington. *Journal of Forestry* **81**, 653–657.

Fosberg MA (1970) Drying rates of heartwood below fiber saturation. *Forest Science* **16**, 57–63.

Frandsen WH (1987) The influence of moisture and mineral soil on the combustion of smoldering forest duff. *Canadian Journal of Forest Research* **17**, 1540–1544. doi:10.1139/X87-236

Hall SA, Burke IC (2006) Considerations for characterizing fuels as inputs for fire behavior models. *Forest Ecology and Management* **227**, 102–114. doi:10.1016/J.FORECO.2006.02.022

Hardwick PE, Lachowski H, Forbes J, Olson R, Roby K, Fites J (1996) Fuel loading and risk assessment for Lassen National Forest. In 'Proceedings of the 7th Forest Service Remote Sensing Applications Conference', 6–10 April 1998, Nassau Bay, TX. (Ed. JD Greer) pp. 328–339. (American Society for Photogrammetry and Remote Sensing: Bethesda, MD)

Hardy CC, Burgan RE, Ottmar RD (2000) A database for spatial assessments of fire characteristics, fuel profiles, and PM_{10} emissions. *Journal of Sustainable Forestry* **11**, 229–244. doi:10.1300/J091V11N01_09

Hartford RA, Frandsen WH (1992) When it's hot, it's hot . . . or maybe it's not! (Surface flaming may not portend extensive soil heating). *International Journal of Wildland Fire* **2**, 139–144. doi:10.1071/WF9920139

Hawkes B, Niemann O, Goodenough D, Lawson B, Thomson A, Sahle W, Fuglem P, Beck J, Bell B, Symington P (1995) Forest fire fuel type mapping using GIS and remote sensing in British Columbia. In 'Proceedings of the Symposium GIS Applications in Natural Resources 2 – The 9th Annual Symposium on Geographic Information Systems', 27–30 March 1995, Vancouver, BC. (Eds M Heit, HD Parker, A Shortreid) pp. 290–299. (GIS World, Inc.: Fort Collins, CO)

JMP IN (2003) '*JMP IN 5.1*.' (SAS Institute: Cary, NC)

Keane RE (2008) Surface fuel litterfall and decomposition in the northern Rocky Mountains, USA. USDA Forest Service, Rocky Mountain Research Station, Research Paper RMRS-RP-70. (Fort Collins, CO)

Keane RE, Dickinson L (2007) The Photoload sampling technique: estimating surface fuel loading from downward-looking photographs of synthetic fuelbeds. USDA Forest Service, Rocky Mountain Research Station, General Technical Report RMRS–GTR-190. (Fort Collins, CO)

Keane RE, Garner JL, Schmidt KM, Long DG, Menakis JP, Finney MA (1998) Development of input spatial data layers for the FARSITE fire growth model for the Selway–Bitterroot Wilderness complex, USA. USDA Forest Service, Rocky Mountain Research Station, General Technical Report RMRS-GTR-3. (Ogden, UT)

Keane RE, Burgan RE, Wagtendonk JV (2001) Mapping wildland fuels for fire management across multiple scales: integrating remote sensing, GIS, and biophysical modeling. *International Journal of Wildland Fire* **10**, 301–319. doi:10.1071/WF01028

Keane RE, Frescino TL, Reeves MC, Long J (2006) Mapping wildland fuels across large regions for the LANDFIRE prototype project. In 'The LANDFIRE Prototype Project: Nationally Consistent and Locally Relevant Geospatial Data for Wildland Fire Management'. USDA Forest Service, Rocky Mountain Research Station, General Technical Report RMRS-GTR-175, pp. 367–396. (Fort Collins, CO)

Mark CA, Bushey CL, Smetanka W (1995) Fuel model identification and mapping for fire behavior prediction in the Absaroka–Beartooth Wilderness, Montana and Wyoming. In 'Proceedings: Symposium on Fire in Wilderness and Park Management', 30 March–1 April 1993, Missoula, MT. (Eds JK Brown, RW Mutch, CW Spoon, RH Wakimoto) USDA Forest Service, Intermountain Forest and Range Experiment Station, General Technical Report INT-GTR-320, pp. 227–229. (Ogden, UT)

McKenzie D, Raymond CL, Kellogg L-KB, Norheim RA, Andreu A, Bayard AC, Kopper KE, Elman E (2007) Mapping fuels at multiple scales: landscape application of the Fuel Characteristic Classification System. *Canadian Journal of Forest Research* **37**, 2421–2437. doi:10.1139/X07-056

Menakis JP, Keane RE, Long DG (2000) Mapping ecological attributes using an integrated vegetation classification system approach. *Journal of Sustainable Forestry* **11**, 245–263. doi:10.1300/J091V11N01_10

Mincemoyer SA (2002) FOFEM fuel loading database. On file at the USDA Forest Service, Rocky Mountain Research Station, Missoula Fire Sciences Laboratory. (Missoula, MT)

Ottmar RD, Vihnanek RE, Alvarado E (1994) Forest health assessment: air quality tradeoffs. In 'Proceedings: 12th Conference on Fire and Forest Meteorology', 26–28 October 1994, Jekyll Island, GA. (Eds JD Cohen, JM Saveland, DD Wade) pp. 47–62. (Society of American Foresters: Bethesda, MD)

Ottmar RD, Schaaf MD, Alvarado E (1996) Smoke considerations for using fire in maintaining healthy forest ecosystems. In 'The Use of Fire in Forest Restoration'. (Eds CC Hardy, SF Arno) USDA Forest Service, Intermountain Forest and Range Experiment Station, General Technical Report INT-GTR-341, pp. 24–25. (Ogden, UT)

Ottmar RD, Sandberg DV, Riccardi CL, Prichard SJ (2007) An overview of the Fuel Characteristic Classification System – quantifying, classifying, and creating fuelbeds for resource planning. *Canadian Journal of Forest Research* **37**, 2383–2393. doi:10.1139/X07-077

R-Project (2005) Homepage of The R Project for Statistical Computing. Available at http://www.r-project.org/ [Verified 4 May 2009]

Reinhardt ED (2003) Using FOFEM 5.0 to estimate tree mortality, fuel consumption, smoke production and soil heating from wildland fire. In 'Proceedings of the 2nd International Wildland Fire Ecology and Fire Management Congress and 5th Symposium on Fire and Forest Meteorology', 16–20 November 2003, Orlando, FL. (American Meteorological Society: Washington, DC) Available at http://ams.confex.com/ams/pdfpapers/65232.pdf [Verified 4 May 2009]

Reinhardt ED, Keane RE (1998) FOFEM – a First Order Fire Effects Model. *Fire Management Notes* **58**, 25–28.

Reinhardt ED, Keane RE, Brown JK (1997) First Order Fire Effects Model: FOFEM 4.0 user's guide. USDA Forest Service, Intermountain Forest and Range Experiment Station, General Technical Report INT-GTR-344. (Ogden, UT)

Rollins MG, Keane RE, Zhu Z, Menakis JP (2006) An overview of the LANDFIRE Prototype Project. In 'The LANDFIRE Prototype Project: Nationally Consistent and Locally Relevant Geospatial Data for Wildland Fire Management'. (Eds MG Rollins, CK Frame) USDA Forest Service, Rocky Mountain Research Station, General Technical Report RMRS-GTR-175, pp. 1–4. (Fort Collins, CO)

Ryan KC, Reinhardt ED (1988) Predicting post-fire mortality of seven western conifers. *Canadian Journal of Forest Research* **18**, 1291–1297. doi:10.1139/X88-199

Sandberg DV (1980) Duff reduction by prescribed underburning in Douglas-fir. USDA Forest Service, Pacific Northwest Research Station, Research Paper PNW-RP-272. (Portland, OR)

Sandberg DV, Ottmar RD, Cushon GH (2001) Characterizing fuels in the 21st century. *International Journal of Wildland Fire* **10**, 381–387. doi:10.1071/WF01036

Sandberg DV, Ottmar RD, Peterson JL, Core J (2002) Wildland fire in ecosystems: effects of fire on air. USDA Forest Service, Rocky Mountain Research Station, General Technical Report RMRS-GTR-42, Vol. 5. (Ogden, UT)

Shasby MB, Burgan RE, Johnson RR (1981) Broad area forest fuels and topography mapping using digital Landsat and terrain data. In 'Proceedings of the 7th International Symposium on Machine Processing of Remotely Sensed Data', 23–26 June 1981, Purdue University, West Lafayette, IN. (Eds PG Burroff, DB Morrison) pp. 529–537. (Purdue Research Foundation: West Lafayette, IN)

Shiflet TN (Ed.) (1994) 'Rangeland Cover Types of the United States.' (Society of Range Management: Denver, CO)

Sikkink PG, Lutes DC, Keane RE (2009) Field guide for identifying fuel loading models. USDA Forest Service, Rocky Mountain Research Station, General Technical Report RMRS-GTR-225. (Fort Collins, CO)

Taylor SW, Sherman KL (1996) Biomass consumption and smoke emissions from contemporary and prehistoric wildland fires in British Columbia. Canada–British Columbia Partnership Agreement on Forest Resource Development (FRDA II), Pacific Forestry Centre, FRDA Report 249. (Victoria, BC)

Therneau TM, Atkinson EJ (1997) 'An Introduction to Recursive Partitioning using the *Rpart* Routines.' (Mayo Foundation: Rochester, MN)

Valette JC, Gomendy V, Marechal J, Houssard C, Gillon D (1994) Heat transfer in the soil during very low-intensity experimental fires: the role of duff and soil moisture content. *International Journal of Wildland Fire* **4**, 225–237. doi:10.1071/WF9940225

Van Wagner CE (1968) The line intersect method in forest fuel sampling. *Forest Science* **14**, 20–26.

Venables WN, Ripley BD (2002) 'Modern Applied Statistics with *S*.' 4th edn, pp. 251–270. (Springer-Verlag: New York)

Warren WG, Olsen PF (1964) A line intersect technique for assessing logging waste. *Forest Science* **10**, 266–276.

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