Forest Ecology and Management 305 (2013) 248–263

Contents lists available at SciVerse ScienceDirect

Forest Ecology and Management

journal homepage: www.elsevier.com/locate/foreco

Full length article

Evaluating the performance and mapping of three fuel classification systems using Forest Inventory and Analysis surface fuel measurements

Robert E. Keane [a,*], Jason M. Herynk [b,1], Chris Toney [c], Shawn P. Urbanski [d], Duncan C. Lutes [e,2], Roger D. Ottmar [f,3]

[a] USDA Forest Service, Rocky Mountain Research Station, Missoula Fire Sciences Laboratory, 5775 Highway 10 West, Missoula, MT 59808, United States
[b] SEM LLC, 808 Woodford Avenue, Missoula, MT 59801, United States
[c] US Forest Service, Forest Analysis and Inventory Program, Missoula Fire Sciences Laboratory, 5775 Highway 10 West, Missoula, MT 59808, United States
[d] US Forest Service, Rocky Mountain Research Station, Missoula Fire Sciences Laboratory, 5775 Highway 10 West, Missoula, MT 59808, United States
[e] US Forest Service, Fire Modeling Institute, Missoula Fire Sciences Laboratory, 5775 Highway 10 West, Missoula, MT 59808, United States
[f] Pacific Wildland Fire Sciences Laboratory, US Forest Service Pacific Northwest Research Station, 400 North 34th Street, Suite 201, Seattle, WA 98103, United States

A R T I C L E I N F O

Article history:
Received 18 March 2013
Received in revised form 28 May 2013
Accepted 1 June 2013

Keywords:
Fuel loading model
Fuel Characteristics Classification System
Fuel Type Groups
LANDFIRE fuel mapping
Fire effects inputs
Surface fuel loadings

A B S T R A C T

Fuel Loading Models (FLMs) and Fuel Characteristic Classification System (FCCSs) fuelbeds are used throughout wildland fire science and management to simplify fuel inputs into fire behavior and effects models, but they have yet to be thoroughly evaluated with field data. In this study, we used a large dataset of Forest Inventory and Analysis (FIA) surface fuel estimates (n = 13,138) to create a new fuel classification called Fuel Type Groups (FTGs) from FIA forest type groups, and then keyed an FLM, FCCS, and FTG class to each FIA plot based on fuel loadings and stand conditions. We then compared FIA sampled loadings to the keyed class loading values for four surface fuel components (duff, litter, fine woody debris, coarse woody debris) and to mapped FLM, FCCS, and FTG class loading values from spatial fuel products. We found poor performances (R^2 < 0.30) for most fuel component loadings in all three classifications that, in turn, contributed to poor mapping accuracies. The main reason for the poor performances is the high variability of the four fuel component loadings within classification categories and the inherent scale of this variability does not seem to match the FIA measurement scale or LANDFIRE mapping scale.

Published by Elsevier B.V.

1. Introduction

Fuel classifications have been used extensively in wildland fire science and management to simplify fuel inputs into fire behavior and effects models (Burgan, 1987; Keane, 2013). Wildland fuels are the dead and live biomass available for fire ignition and combustion (Albini,1976; Sandberg et al., 2001). In most fuel classifications, fuel particles are stratified into unique categories called fuel components (Table 1), such as duff, litter, and shrubs, and each component is assigned attributes based on the input requirements of fire software applications (e.g., Anderson, 1982; Arroyo et al., 2008; Deeming et al., 1977). There are many fuel component attributes, such as heat content, mineral content, and density, but the most commonly used attribute across most fire management applications is fuel loading or the biomass per unit area (Brown and Bevins, 1986; Harmon et al., 1986; Pyne et al., 1996). Fuel loads are required as inputs to nearly all fire applications (Burgan, 1987; Krivtsov et al., 2009), and they are also important for the quantification of carbon inventories (de Groot et al., 2007), site productivity (Neary et al., 1999), and wildlife habitat (Ucitel et al., 2003). This paper evaluates three surface fuel classifications used for the prediction of fire effects, such as fuel consumption, smoke production, and soil heating, that describe actual fuel loadings on the ground and can, therefore, also be used for fuel description, inventory, and monitoring.

Two fuel loading classifications are commonly used in fire management applications to predict fire effects. Fuel Loading Models (FLMs) identify fuel classes designed specifically for predicting unique fire effects (Lutes et al., 2009). There are 27 FLMs, which are mutually exclusive by design, yet intended to coarsely represent the range of surface fuel conditions encountered across the contiguous United States (Sikkink et al., 2009). The Fuel Characteristic Classification System (FCCS) (Ottmar et al., 2007; Riccardi et al., 2007a, 2007b) was developed to provide managers with a conceptual framework to construct fuelbeds that describe biomass across both surface and canopy fuel components. We also created a

* Corresponding author. Tel.: +1 406 329 4760; fax: +1 406 329 4877.
E-mail addresses: rkeane@fs.fed.us (R.E. Keane), jherynk@fs.fed.us (J.M. Herynk), ctoney@fs.fed.us (C. Toney), surbanski@fs.fed.us (S.P. Urbanski), dlutes@fs.fed.us (D.C. Lutes), rottmar@fs.fed.us (R.D. Ottmar).
[1] Tel.: +1 406 728 7130.
[2] Tel.: +1 406 329 4761.
[3] Tel.: +1 (206) 732 7826.

0378-1127/$ - see front matter Published by Elsevier B.V.
http://dx.doi.org/10.1016/j.foreco.2013.06.001

Table 1
Descriptions of commonly used surface fuel components.

General fuel type	Fuel component	Common name	Size	Description
Downed Dead Woody	1 h woody	Twigs	<1 cm (0.25 inch) diameter	Detached small woody fuel particles on the ground
	10 h woody	Branches	1–2.5 cm (0.25–1.0 inch) diameter	Detached small woody fuel particles on the ground
	100 h woody	Large branches	2.5–7.6 cm (1–3 inch) diameter	Detached small woody fuel particles on the ground
	1000 h woody	Logs, Coarse woody debris (CWD)	7.6+ cm (3+ inch) diameter	Detached small woody fuel particles on the ground
	Fine woody debris (FWD)	Twigs, branches, and large branches	0–7.6 cm (0–3 inch) diameter	Combined 1, 10, 100 h fuel loadings
Duff	Duff	Duff	All sizes	Partially decomposed biomass whose origins cannot be determined
Litter	Litter	Litter	All sizes excluding woody	Freshly fallen non-woody material which includes leaves, cones, pollen cones,
Total	All fuels	Total surface fuel load (TSFL)	All surface fuels	All material on the ground

new Fuel Type Group (FTG) classification based on the forest type groups of the Forest Inventory and Analysis (FIA) program for simulating emissions from fires across the US by summarizing fuel component loadings from FIA plots by the 20 classes in the forest type group classification (Ruefenacht et al., 2008). Each of these classifications are different in that they were built using uniquely different approaches; FLMs were developed using a top–down clustering approach to identify distinct classification categories; FCCSs were created using a bottom–up approach by sampling characteristic fuelbeds on the ground that then become a classification class; and FTGs summarize fuel loadings by forest types (Keane, 2013). None of these classifications have been formally tested for performance and accuracy.

The FLM and FCCS classifications were mapped at 30 m pixel resolution to describe fuel loadings across the contiguous United States in the National LANDFIRE Project (Reeves et al., 2009; Rollins, 2009) and the FTG classification was mapped to forest type groups at 250 m resolution using the Remote Sensing Applications Center (RSAC) FIA forest type group mapping effort (Ruefenacht et al., 2008). The LANDFIRE FLM and FCCS maps are used extensively in fire management planning projects, such as prioritizing, designing, and implementing fuel treatment projects (Reynolds et al., 2009). Yet, despite their widespread use, these fuel classification maps have not been thoroughly assessed for accuracy and precision at fine scales (plot-level) because of a lack of extensive ground data (Reeves et al., 2009). Recently, the Forest Inventory and Analysis (FIA) program, under an agreement, made available an extensive set of surface fuel data for forested areas for several states in the western United States consisting of georeferenced plot measurements of the surface fuel component loadings.

In this study, we used the extensive FIA surface fuels data for the western US to evaluate the performance of the FLM, FCCS, and FTG classifications and to estimate the accuracy and precision of the LANDFIRE FLM and FCCS geospatial maps and the FTG map developed from the RSAC forest type group layer. There are limitations and weaknesses to all three classifications (Keane, 2013), so we wanted to assess whether these limitations jeopardized the application of the classifications in fire management, and to assess whether the limitations propagated to the digital maps. The problem in the past has always been a lack of high quality, georeferenced fuel data for reference in development, validation, and testing of fuel classifications (Keane, 2013). These new FIA fuels data provided an excellent source for assessing the utility and accuracy of the FLM, FCCS, and FTG classifications, along with an extensive reference for validating the LANDFIRE and RSAC FTG map products. At the same time we recognize that the plot-level FIA fuels data also contain high uncertainty that might influence this evaluation (Westfall and Woodall, 2007).

1.1. FLMs

The FLMs of Lutes et al. (2009) are distinctive in that they were created using field-collected fuel loading data from 4000+ plots located across the contiguous United States that were then used as inputs to FOFEM to simulate smoke emissions and soil heating. The simulation results for all 4000+ plots were clustered to identify unique "effects groups", then a comprehensive key based on loading was created using regression tree analysis to objectively identify the classification category for a field-assessed observations. As a result, this classification integrated the resolution of the fire effects models into the FLM classification design and used easily obtained field measures in the field key. This direct, top–down approach partitions variation in the field data to reduce redundancy and produce an effective classification that can be used in the field. Fuel loading values were assigned to each FLM as the median fuel loading across all plots in that class (Table 2). FLM development was supported by the LANDFIRE prototype project to create a national map describing fuel loadings for fire effects prediction (Keane et al., 2007). FLMs can be used as (1) inventory techniques to quantify fuel characteristics (Sikkink et al., 2009); (2) classifications of unique fuel types to facilitate communication between

Table 2
The median fuel loadings (kg m^{-2}) assigned to each of six surface fuel components for each forested FLM used in this study. FLM classification has a total of 27 classes, but classes 014, 015, 053, 065, and 066 are non-forest FLM (Sikkink et al., 2009).

FLM	Effects group	Litter	Duff	1 h	10 h	100 h	1000 h
		Median loading (kg m^{-2})					
011	01	0.04	0.00	0.01	0.02	0.01	0.00
012	01	0.06	0.00	0.06	0.35	0.60	0.58
013	01	0.56	0.27	0.05	0.34	0.46	0.50
021	02	0.26	0.74	0.04	0.14	0.15	0.21
031	03	0.42	1.64	0.06	0.20	0.24	0.34
041	04	0.54	0.00	0.06	0.37	0.58	0.58
051	05	0.34	3.55	0.04	0.25	0.32	0.32
061	06	0.20	0.81	0.06	0.29	0.55	3.75
062	06	0.30	4.61	0.03	0.21	0.28	0.36
063	06	0.34	3.82	0.04	0.31	0.53	1.74
064	06	0.65	5.80	0.07	0.25	0.37	0.75
071	07	0.49	2.10	0.10	0.32	0.49	2.58
072	07	0.85	3.76	0.09	0.23	0.30	0.64
081	08	0.20	0.89	0.07	0.26	0.60	8.15
082	08	0.85	3.97	0.12	0.35	0.71	2.70
083	08	0.56	2.67	0.11	0.36	0.64	5.03
091	09	0.26	10.30	0.07	0.32	0.37	0.65
092	09	0.68	3.33	0.12	0.36	0.74	10.34
093	09	1.39	7.36	0.13	0.31	0.54	4.82
101	10	2.24	22.42	0.09	0.21	0.24	0.36
102	10	4.03	2.35	0.03	0.11	0.24	1.03

managers, scientists, and other professionals (Sandberg et al., 2001); and (3) map units in fuel mapping efforts (Reeves et al., 2009). There were insufficient data for some FLM classes and the FLM analysis was missing critical data from several major US fuelbeds that were unsampled at the time of FLM development, such as non-forest rangelands and rare forest types (Lutes et al., 2009).

1.2. FCCS

The FCCS uses an indirect, bottom–up approach for quantifying unique fuelbeds and associated fuelbed categories and subcategories (Ottmar et al., 2007). In this flexible classification, fuelbeds are added into FCCS as they are identified by managers, scientists, and resources specialists to account for succession, management, and disturbance history for local, regional, or national applications (Berg, 2007); new fuel conditions are sampled in the field and these data become a new fuelbed in the FCCS (Riccardi et al., 2007a). The FCCS also contains its own surface fire spread model adapted from Rothermel (1972) to simulate surface fire behavior using FCCS fuelbed data (Sandberg et al., 2001).

A national fuelbed database within the FCCS, compiled from published and unpublished literature, fuels photo series, fuels data sets, and expert opinion, was created to represent a particular scale of interest. This set of national fuelbeds is referred to as FCCSs in this paper and it was intended to represent broad vegetation types and change agents (e.g., wildfire, insects and disease) throughout the contiguous United States. They are mapped at regional and national scales (McKenzie et al., 2007), but for site-specific applications, such as prescribed burn planning, the FCCS fuelbed should be customized with local field data. FCCS fuelbeds are datasets that represent the physical characteristics of a diverse set of wildland fuels from canopy characteristics (e.g., percent cover and height of trees) to surface fuels (e.g., percent cover and depth of duff). Because fuel loadings are calculated from input fuelbed characteristics and FCCS fuelbeds were developed to represent the structure and composition of wildland fuels, there is likely high "redundancy" in the fuel loading values between FCCS classes.

1.3. FTG

We used the recently available FIA fuels data to assemble a new fuel classification system to develop fire emission inventories and eventually predict real-time emissions (Urbanski et al., 2011). The Fuels Type Group (FTG) classification was built by summarizing fuelbed component loadings by FIA forest type groups using the new FIA fuels data (Table 3). We created the FTG classification by extracting the forest type group variable for each FIA plot (Arner et al., 2003) and computing the mean loading for each fuel component for each forest type group using the keyed FIA fuels data (Table 3). FTG classes were given the same name as the corresponding forest type group. We included this new classification in our analysis to represent those fuel classifications that are based on vegetation types (Keane et al., 2001) and to evaluate the performance of a classification that was created using the same data as was used for the comparison (i.e., best case scenario). However, FTGs are summarized to vegetation types (Forest Type Groups) and it has been shown that fuels are rarely correlated to vegetation composition (Brown and Bevins, 1986; Keane et al., 2012b).

1.4. Classification mapping

FLMs were mapped by the LANDFIRE project using the following protocol: (1) available FIA fuels plots were keyed to an FLM value using Sikkink et al. (2009) key; (2) FIA plots and their assigned FLMs were matched to combinations of existing vegetation type, existing vegetation cover, and existing vegetation height; and (3) a FLM class was systematically assigned to each pixel using a cross-walk approach where all possible pixels were assigned a FLM by vegetation type/cover/height hierarchical combinations. Because there were few data to assign a FLM to all combinations, pixels were assigned a FLM by using more general vegetation type/cover, or type/height combinations, and finally by a broad existing vegetation type group classification (Reeves et al., 2009). Approximately 75% of the FIA plots used in this study were also used by LANDFIRE to assign FLMs to LANDFIRE classification class combinations.

FCCS fuelbeds were mapped by the LANDFIRE project based on the existing vegetation type classification (McKenzie et al., 2012). For certain vegetation types, multiple FCCS were available that reflected certain seral stages of the vegetation, and, in these cases, cover and height values were used to assign separate FCCS fuelbeds. Post-disturbance vegetation types were assigned a "custom" set of FCCS fuelbeds because there were few post-disturbance FCCS fuelbeds (Reeves et al., 2009).

Scientists at the USDA Forest Service RSAC and FIA mapped forest type groups for the conterminous US and Alaska with a spatial resolution of 250 m and an overall accuracy of 64% for the western US (Ruefenacht et al., 2008; http://fsgeodata.fs.fed.us). In the western conterminous US, 17 forest type groups were mapped with an area >10,000 ha; however, 12 forest type groups account for 98.6% of total mapped forest area. Ten forest type groups comprised 99% of forest burned area in the western conterminous US from 2003 to 2010 (MTBS, 2012). These 10 groups included 9 of the 10 most commonly mapped groups. We assigned the FTG summarized loadings to each forest type group to create the FTG map.

1.5. Project objectives

The primary objective of this study was to assess the performance and accuracy of three fuel classification systems (FLM, FCCS, and FTG) and their associated maps using field-measured FIA fuels data. This primary objective was achieved through three separate tasks:

- *Assess classification performances*: This was done by keying an FTG, FLM and FCCS class for each FIA plot using the appropriate keys and then comparing FIA measured fuel component loadings with the component loadings associated with that keyed class.
- *Assess emission predictions*: This involved computing PM2.5 (fine particulate matter) emissions for each FIA plot and each class in the three classifications, and then comparing emissions rather than loadings of the FIA plot to the keyed FLM, FCCS, and FTG class for that FIA plot. We did this because emissions prediction is the most common FLM, FCCS, and FTG application.
- *Assess map accuracies*: This was done by comparing keyed FIA plot classification classes with mapped classification class and by comparing FIA measured fuel component loadings with loadings of mapped classification class for the FIA plot location.

This study was intended to provide context and background for those who plan on using FLMs, FCCSs, and FTGs in the field, and those who plan on using the FLM and FCCS LANDFIRE maps and FTG RSAC-based maps in their fire management activities.

2. Methods

In summary, we compiled a surface fuels dataset from the FIA database by selecting specific FIA plots that met our evaluation criteria as described below. We then keyed the FLM, FCCS, and FTG classes for each selected FIA plot from the sampled fuels and

Table 3
The mean fuel loadings (kg m^{-2}) associated to each of the six fuel components assigned to each Forest Type Group to create the Fuel Type Group (FTG) classification.

FTG	FIA FTG variable	Percent of forest[a]	n	Litter	1 h	10 h	100 h	1000 h	Duff
180	Pinyon/juniper group	23.0	1875	0.45	0.02	0.05	0.16	0.25	0.39
200	Douglas-fir group	22.3	2498	0.75	0.04	0.15	0.52	2.22	1.68
220	Ponderosa pine group	12.6	1327	1.35	0.01	0.08	0.26	0.92	1.49
240	Western white pine group	0.1	23	1.01	0.01	0.05	0.16	1.78	1.37
260	Fir/spruce/mountain hemlock group	16.1	1813	0.6	0.03	0.12	0.4	2.62	1.91
280	Lodgepole pine group	7.2	860	0.96	0.02	0.09	0.38	1.97	2.3
300	Hemlock/Sitka spruce group	1.9	397	0.72	0.03	0.16	0.51	5.93	3.04
320	Western larch group	0.2	104	1.39	0.04	0.16	0.63	3.06	3.62
340	Redwood group	0.3	55	3.46	0.03	0.15	0.52	4.52	3.09
360	Other western softwoods group	1.2	598	0.67	0.01	0.05	0.13	0.46	0.87
370	California mixed conifer group	5.0	782	1.95	0.02	0.14	0.43	2.07	2.37
700	Elm/ash/cottonwood group	0.1	29	1.28	0.03	0.18	1.12	1.17	3.4
900	Aspen/birch group	3.3	302	1.24	0.02	0.09	0.49	1.07	3.21
910	Alder/maple group	0.9	189	2.45	0.02	0.14	0.49	2.77	3.81
920	Western oak group	5.2	1084	1.79	0.02	0.09	0.27	0.54	1.45
940	Tanoak/laurel group	0.8	229	2.62	0.03	0.15	0.48	2.02	3.32
950	Retired (Other western hardwoods group)	0.8	89	0.8	0.02	0.06	0.15	0.13	0.81
960	Other hardwoods group	0.0	78	2.22	0.02	0.1	0.37	1.18	2.01
970	Woodland hardwoods group	0.0	67	1.31	0.01	0.1	0.27	0.56	1.34
999	Nonstocked	NA[b]	739	0.62	0.01	0.06	0.2	0.66	0.67

[a] Percent of total forest area in western CONUS mapped as this classification by the RSAC/FIA forest type group map (see text).
[b] Nonstocked was not a classification in the RSAC/FIA map of forest type groups.

vegetation data. And, for each FIA plot location, we determined the mapped FLM, FCCS, and FTG by taking the value of a single pixel at the FIA plot location. We then compared the FIA-keyed FTG, FLM and FCCS values to the mapped values, and more importantly, we compared the FIA-measured loadings of the four fuel components to loadings of the mapped FLM, FCCS, and FTG classes. We used a combination of contingency table, regression, and accuracy assessment statistical techniques to compare results. We compared FIA loadings to median FLM and mean FTG values because most management applications use these values to simulate fire effects.

This paper will confine its discussion to loading or the dry weight biomass of fuel per unit area (kg m^{-2}) of four major surface fuel components: litter, duff, fine woody debris (FWD; 0–7.6 cm diameter), and coarse woody debris (CWD, 7.6+ cm diameter; also called logs or 1000 h fuels) (Table 1). While shrub and herb components are included in the FLM and FCCS classifications, only cover and height were sampled at the FIA plots for these components so they were not included in this study. We combined 1, 10, and 100 h downed woody fuel loadings into one FWD loading because of the low and highly variable loadings for each of the individual fine woody components (Table 1).

2.1. Study area

The geographic scope of this project includes eight states in the western United States, covering the Pacific Northwest and Interior West FIA regions (Fig. 1). The scope was limited to states where FIA fuels data were available, which included Arizona, California, Colorado, Idaho, Montana, Oregon, Utah and Washington. No FIA fuels data were available at the time of analysis for Wyoming, Nevada and New Mexico.

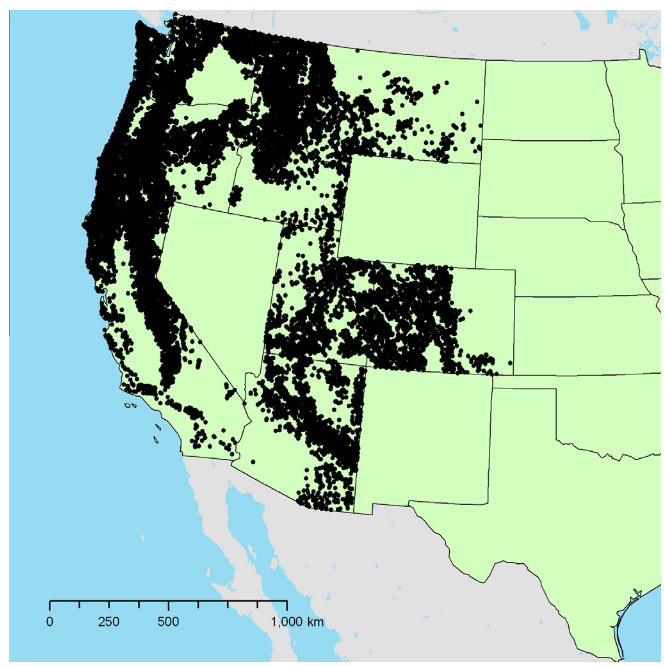

Fig. 1. The approximate FIA plot locations for all plots used in this study.

2.2. FIA sampling and data compilation

The FIA program applies a three-phase sampling design covering all ownerships across the USA using a hexagonal grid with approximately one permanent plot per 2,428 ha (Bechtold and Patterson, 2005). Phase 1 sampling is designed to reduce variance of population estimates through stratification based on remotely sensed forest cover at plot locations. Only forested land is included in the inventory and it is defined as areas at least 10% stocked with tree species, or land formerly having such tree cover and not currently developed for a non-forest use, at least 4000 m^2 in size, and at least 36.6 m wide (Bechtold and Patterson, 2005). Phase 2 sampling refers to the detailed measurements made at each plot location.

Inventory plots consist of four 7.32-m fixed-radius subplots spaced 36.6 m apart in a triangular arrangement with subplot 1 in the center and subplots 2, 3, and 4 at azimuths of 0°, 120°, and 240°, respectively, from the center of subplot 1 (USDA Forest Service, 2007, Woodall et al., 2010) (Fig. 2). The plot footprint, defined as the minimum circle enclosing all four subplots, is approximately 6000 m^2. Phase 3 sampling is done on a 1/16th subset of the Phase 2 plots and includes additional measurements associated with forest health such as such tree crown condition, soil conditions, lichen community composition, understory vegetation, and down woody material (Bechtold and Patterson, 2005; Woodall and Monleon, 2008; Woodall et al., 2011) (Fig. 2). Since Pacific Northwest and Interior West FIA units began measuring down woody material on all their Phase 2 plots in 2001 and 2006, respectively, and compiled Phase 3 data for the entire USA are not yet available, the present study used the available Phase 2 sample for the western USA only.

Woody fuels were tallied by particle diameter size classes commonly used by fire management and fire behavior computer programs (Table 1). Measurement protocols included planar intersect transect sampling for FWD and CWD, and systematic point sampling for duff and litter depths (Brown, 1974; Woodall et al., 2010). Transect and point sample locations were different for plots in the Pacific Northwest FIA region (California, Oregon, Washington) from plots in the Interior West FIA region (Arizona, Colorado, Idaho, Montana, Utah). In the Pacific Northwest, two CWD transects originated at each subplot center and extended out 17.95 m horizontal distance at azimuths of 150 and 270 degrees from center in subplots 1 and 4, and 30° and 150° from center in subplots 2 and 3 (Fig. 2). Only one FWD transect was established in each subplot at 150° azimuth that began at 4.27 m slope distance from subplot center and extended 1.83 m slope distance for the 1-h and 10-h samples and 3.05 m slope distance for the 100-h sample, for total transect lengths of 7.32 m and 12.2 m slope

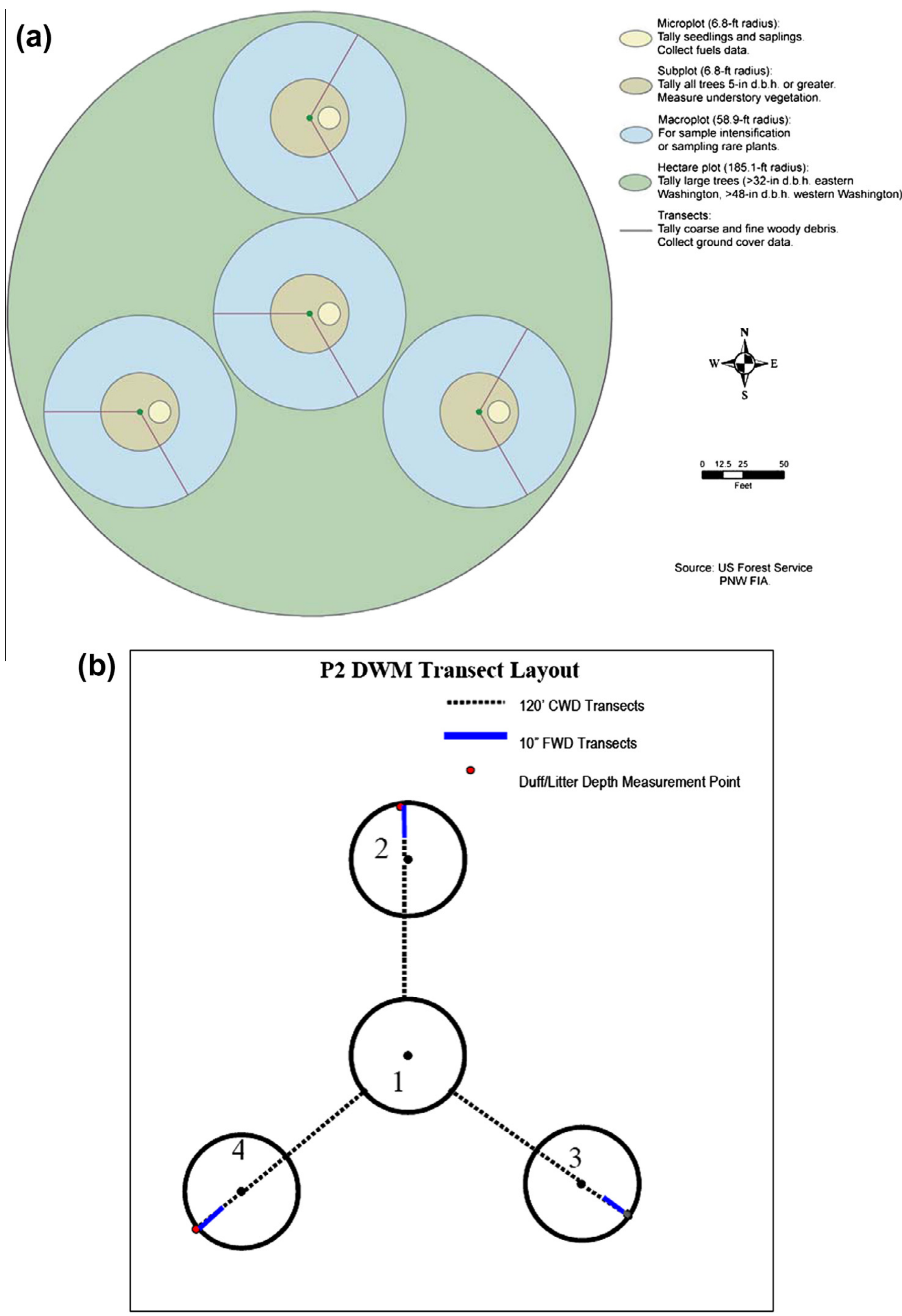

Fig. 2. FIA plot layout for surface fuel loading sampling.

distance. Litter and duff sample points were at 7.32 m slope distance from the beginning of each CWD transect for a total of eight sample points per plot. The Interior West plots (Fig. 2) had three CWD transects oriented at azimuths of 0°, 120°, and 240° from center of subplot 1, beginning at the perimeter of subplot 1 and extending 36.58 m horizontal distance across the centers of subplots 2, 3, and 4. Three FWD transects were located along at ends of the CWD transects in subplots 2, 3, and 4 with transect lengths of 1.83 m slope distance for the 1-h and 10-h and 3.05 m slope distance for the 100-h samples. Litter and duff sample points were located at the end of each CWD transect for a total of three sample points per plot.

FIA sampling protocol specified CWD as pieces, or portion of pieces, of down dead wood with a minimum small-end diameter of at least 7.62 cm at the point of transect intersection, and a length of at least 0.91 m. CWD pieces were detached from a bole and not supported by a root system with a lean angle >45° from vertical (Woodall and Monleon, 2008; Woodall et al., 2010). Information collected for every CWD piece intersected by transects included diameter at the transect intersection, decay class (Lutes et al., 2006), and species. The piece length, small-end diameter, and large-end diameter were also measured in Pacific Northwest plots. Decay class was a subjective determination of the amount of decay present in an individual log (class 1 – least decayed to class 5 – extremely decayed). Species of each fallen log was identified through determination of species-specific bark, branching, bud, and wood composition attributes (excluding decay class 5).

Biomass estimates of CWD, FWD, litter, and duff were calculated using estimators detailed in Woodall and Monleon (2008) and summarized briefly here. For CWD in Pacific Northwest plots, volume was calculated for every piece using end diameters and length for pieces in decay classes 1–4, and using intercept diameter and length for pieces in decay class 5. Volume was converted into biomass through the use of decay reduction factors and bulk density based on the species and decay class of each piece (Harmon et al., 2008). For CWD in Interior West plots, biomass was calculated using intercept diameters of each piece along with the bulk densities and decay-reduction constants in an equation for the plot on a per unit area basis (Woodall and Monleon, 2008). Volumes of FWD were estimated per unit area using quadratic mean diameters based on FIA forest type (Woodall and Monleon, 2010), and then converted to biomass using bulk density values for FIA forest types (Woodall and Monleon, 2008) and a default decay reduction factor of 0.8. Duff and litter biomass were calculated by multiplying average depth of the sample points in the plot by the bulk density and a unit conversion factor.

We used plots from the Pacific Northwest and Interior West FIA regions measured during 2001–2009 that had fuel loading data available and a single forest condition class described across all four subplots (Woudenberg et al. 2010). We overlaid the plot locations on the LANDFIRE disturbance layers for 1999–2008 to identify plots that were disturbed after the plot measurement date and omitted disturbed plots since they likely would not represent conditions depicted on the circa 2008 LANDFIRE fuel maps. We used a total of 13,138 FIA plots to evaluate the FCCS and FLM classifications and maps (Fig. 1).

2.3. Fuel classification of FIA data

Sikkink et al. (2009) key was used to identify most appropriate FLM class for each FIA plot from the loadings of duff, litter, logs, and FWD. All FIA plots were successfully keyed to a forested FLM. Because FLMs characterize a large range of fuels, median loading values were used for each of the four components in our comparisons (Table 2). The FLM key had previously been coded in the JMP IN statistical software package (JMP IN, 2003) for the original FLM publication (Lutes et al., 2009), so all FIA fuel data were imported into JMP to key FLM for each plot and then exported from JMP using the unique plot identifier and the plot location data.

We used LANDFIRE refresh mapping rule sets detailed in Reeves et al. (2009) to assign an FCCS type to a FIA plot using vegetation type, vegetation cover, and vegetation height by LANDFIRE mapping zone. Additionally, these rule sets accounted for disturbance, severity, and time since last disturbance. We assigned 10,471 of the 13,138 plots an FCCS category; the other 2667 were removed because the FIA plot characteristics didn't match an available rule set, often because vegetation cover was less than 10%. Once an FCCS was assigned to an FIA plot, we derived measurements of the four fuel component loadings using a lookup table provided by the Fire and Environmental Research and Applications Team (http://www.fs.fed.us/pnw/fera/fccs/).

FTGs were already keyed to FIA plots based on the RSAC FIA forest type group classification (Arner et al., 2003). Every FIA plot has an assigned FTG value and this value was matched to the FTG values in Table 3. There is some inherent bias because the FTGs fuel classification was created with the same data used for this assessment, but we thought the results would be informative and useful to fire management since it represented a best-case scenario for accuracy.

We extracted the mapped FLM, FCCS, and FTG values by overlaying FIA plot locations on the LANDFIRE Refresh 2008 and RSAC forest type group data layers. We selected the classification class by taking the pixel value for each plot location. The RSAC forest type group has a pixel resolution of 250 m, comparable to the resolution of the FIA plot footprint; the FTG assessment used the RSAC map pixel in which each FIA plot was located.

2.4. PM2.5 emission simulations

A major management application for all three fuel classifications is the computation of smoke emissions so we also performed an assessment of PM2.5 emissions computed from the FIA fuelbed compared to the emissions computed using the classification fuelbed. Emission flux (kg m^{-2}) of the pollutant PM2.5 from wildland fire was estimated as the product of the fuel load consumed (kg-dry vegetation burned m^{-2}) and an emission factor for PM2.5 (kg-dry vegetation $burned^{-1}$) (Urbanski et al., 2011 and references therein). To compute PM2.5 emissions, we used the FOFEM model (Reinhardt et al., 1997; www.firelab.org) to simulate consumption of all four surface fuel components at each FIA plot using the FIA measured fuel loadings and the keyed classification fuel loadings. Other FOFEM inputs used in these simulations are (1) fuel moistures set at 10-h = 10%, 1000-h = 15%, and duff = 40%, and (2) canopy fuels, herbs and shrubs were set to zero due to lack of data.

2.5. Analysis

To assess performance of FLMs and FCCSs, we compared the surface fuel loading values for each of the four components and for the total surface fuel loading (TSFL) for the keyed classification class with the corresponding fuel loading measurements from FIA data. For FLMs, we compared median fuel loadings for each fuel components and TSFL (Table 2) for the FLM class keyed from the FIA data with the measured loadings from that FIA plot. Using univariate regression analysis, we computed measures of model accuracy (R^2, slope, and intercept) by regressing measured FIA loadings with keyed FLM median fuel loadings, and using error analysis, we computed measures of uncertainty (root mean squared error-RMSE, bias as a percent). We repeated this procedure for FCCS and FTGs, and for the smoke emissions predictions. For FCCSs, we compared each of FIA-keyed FCCS fuelbed loadings (see http://

www.fs.fed.us/pnw/fera/fccs/) to the FIA measured surface fuels loadings for the same fuel components. For FTGs, we compared the average loadings for the fuel components in each FTG class (Table 3) with the FIA loading measurements. We also compared the keyed FLM and FCCS component loadings using the same statistical tests to evaluate if they correlate with each other. To evaluate classification performance, we compared fuel component means for all classification classes to FIA loadings for those classes with 50 or more keyed FIA plots (20 FLM models, 31 FCCS models, and 12 FTG models) using three statistical tests (percentile bootstrap, Welch, Wilcox). We included TSFL in some of the analysis to evaluate if differences in performance and mapping were due to the stratification of fuel loadings by component.

To assess LANDFIRE and FTG fuel map accuracy, we used contingency analysis to test for dependence of mapped classification on the field-based FIA classification. We summarized relationships with a contingency table analysis and tested for statistical significance using chi square tests. We also estimated the K_{hat} statistic for each accuracy assessment. We analyzed the predictive power of the mapped values for the FIA values (how well are FIA data represented by the mapped fuel classifications) using methods similar to those used for the classification assessment. The same regression and error analyses techniques used to evaluate classification performance were also used to compare the mapped FLM median, FCCS fuelbed loadings, and FTG mean loadings (predicted) to the FIA loading data (observed). We summarized regression and contingency statistics in both tabular and graphic formats.

3. Results

3.1. Classification performance

One measure of classification performance is the differentiation of fuel component loadings across keyed classification classes, and from our study results, we found many significant differences ($p < 0.05$) in the mean of the FIA measured fuel loadings across the majority of classes for all classifications (Figs. 3–5). There were 20 FLM classes (Table 2) that had more than 50 plots providing 380 possible combinations, and for litter, only 20 of these combinations had mean values that were statistically the same ($p < 0.05$); the FLM classification differentiated the mean plot litter loading about 82% of the time (360 of 380 combinations) (Fig. 3). FLMs had the best performance of all classifications for duff and CWD, with 96% and 92% of the model combinations having significantly different ($p < 0.05$) mean loadings, respectively. FCCS had the lowest rate of differentiation for all fuel components (Fig. 4). FTGs were the top performer for litter and FWD with differentiation rates of 92% and 69%, respectively (Fig. 5). All classifications had the poor performance for FWD loading (>70%). Box-plots of fuel component loading for the 12 most prominent FTGs (according to the RSAC/FIA forest type group map) show poor differentiation between most of the 12 classes for FWD.

A better test of classification performance is how well the measured FIA fuel component loading values compared with the keyed FLM, FCCS and FTG class component loadings (Table 4). For FLMs, we found that FIA measured loadings compared well for duff and CWD with $R^2 > 0.70$ and slopes ranging from 0.98 to 1.02 (a slope of 1.0 indicates good agreement), but there were few agreements between observed and predicted loadings for litter and FWD with computed R^2 values quite low (<0.20) and regression slopes mostly less than 0.88 indicating most loadings were under predicted (Table 4). In addition, intercepts were statistically ($p < 0.05$) different from zero (>0.16 kg m^{-2}), the bias for litter was greater than 148% of the mean, and the RMSE values were high (>0.5 kg m^{-2}) (Fig. 6).

FCCS and FTG classification performances were poorer than FLM performance with no fuel component having an R^2 value greater than 0.27 and all slopes less than 0.27 (Table 4). All FCCS fuel component loadings were under-predicted (Fig. 7) with negative bias values greater than 28% of the mean, while bias for FTGs were significantly lower (0.01–0.26%) (Fig. 8). Both FCCS and FTG classifications had high RMSEs (0.54–16.3) and high intercepts (>0.44). There was no apparent relationship between keyed FLM and keyed FCCS using the FIA loadings (Table 4).

We found that the FLM classification performed better than FCCS and FTG classifications when we compared the computed PM2.5 smoke emissions of the FIA plots with the computed PM2.5 smoke emissions for the loadings for the classification classes (Table 5). The FLM emissions had a better fit ($R^2 = 0.74$), higher slope (0.73), and lower RMSE (534), than the FCCS ($R^2 = 0.12$, slope = 0.37, RMSE = 1198) and FTG ($R^2 = 0.21$, slope = 0.21, RMSE = 837).

3.2. Map accuracy

We found low map accuracies for all three fuel classifications. The LANDFIRE mapped FLM categories for the FIA plot locations matched the keyed FLM categories from the FIA data only 25% ($K_{hat} = 0.098$) of the time (Table 6). FLM categories with lighter fuel loadings (11–31) had the best agreement (4–67% agreement), while those FLMs with heavy log and duff loadings (classes 63–102) had poor agreement (0–19% agreement) (Table 6). The lightest load FLM 011 had both the highest agreement (67%) and highest number of plots (3016), while the next most frequent FLMs (021, 031) had high plot numbers (1847, 1856 respectively) but low accuracies (<22%). Over 57% of the FIA plots were classified to these three classes (011, 021, 031) thus explaining the lower K_{hat} (0.098). Five FLMs (041, 062, 083, and 091, and 102) did not have any FIA plot classified correctly, probably because of their rarity on the landscape and the low number of FIA plots for these categories (635 plots). In general, omission error was greater than commission error for most FLMs.

FCCS and FTG mapped class values compared better than mapped FLM classes to the FIA keyed classes (FCCS was 34% agreement, $K_{hat} = 0.33$ and FTG was 64% agreement, $K_{hat} = 0.54$). However, this was probably because the key that was used to assign FCCS classes to combinations of LANDFIRE vegetation composition and structure (cover, height) layers was also used to assign FCCS categories from FIA data and the same is true for FTGs (forest type groups were used to key FIA plots). Therefore, the FCCS 34% and FTG 64% agreements reflect the accuracy of the LANDFIRE vegetation and RSAC forest type group layers rather than the fuel maps. FCCS results were similar to FLMs in that many plots (4661 of 10470) were in few categories (20% in FCCS 4, 12% in FCCS 9, 12% in FCCS 210), and these categories had poor agreement (<25%). There were several FCCS categories that had a high number of plots (>500) and high agreement including FCCS 210 (1262 plots and 67% agreement), FCCS 70 (530 plots and 63%), FCCS 21 (507 plots and 40% agreement). Interestingly, only six of the 55 mapped FCCSs did not have any FIA plots correctly mapped, and only 11 of the mapped FCCSs had less than 10 FIA plots. We did not include a FCCS and FTG contingency table because of the high number of classes (55 FCCS mapped classes).

A better measure of map accuracy is to compare measured FIA fuel loadings to the loadings of the mapped FLM, FCCS, and FTG classes. Here, results are even less promising (Table 7and Figs. 9–11). Agreement between mapped FLM and FIA loadings are poor ($R^2 < 0.1$). Slopes of the regression line reveal severe under prediction for all FLM components (<0.24) (Fig. 9) and FTG components (<0.20) (Fig. 11), but are somewhat close to 1.0 for FCCS loadings (0.1–1.4) (Fig. 10). However, bias for mapped FCCS loadings (39–811%) are much greater than FLM loadings (−73–18%) and FTG loadings (−3.5–0.89%), and RMSE values are higher for FCCS (1.46–22.54) than for FLM (0.66–3.53) and FTG (0.98–2.42) (Table 7). As expected, mapped FCCS fuelbed loadings compared

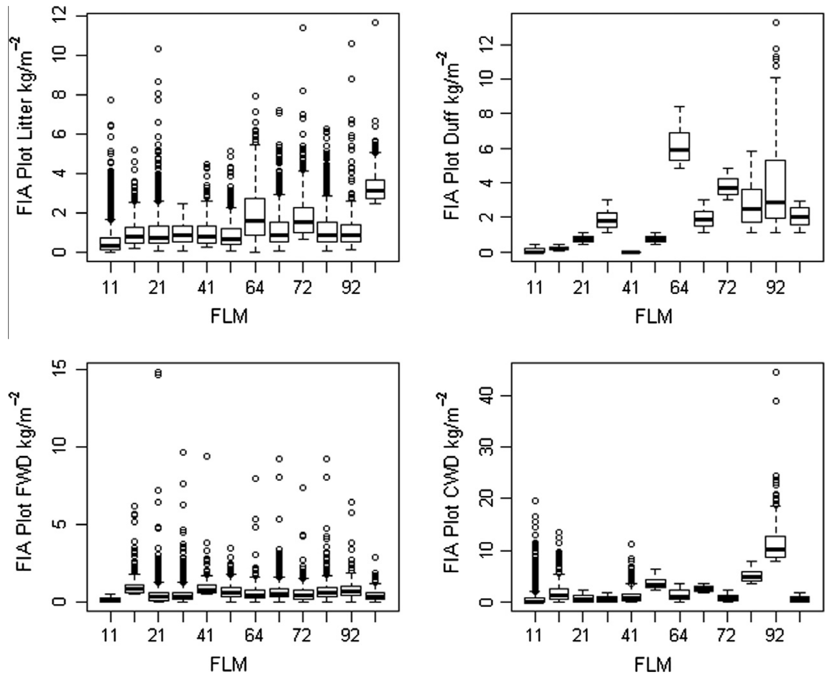

Fig. 3. The 12 most common FLM classes keyed for each FIA plot compared to the measured fuel loading for the same plot for the four fuel components: (a) litter, (b) duff, (c) FWD and (d) CWD (see Table 1 for definitions of fuel components).

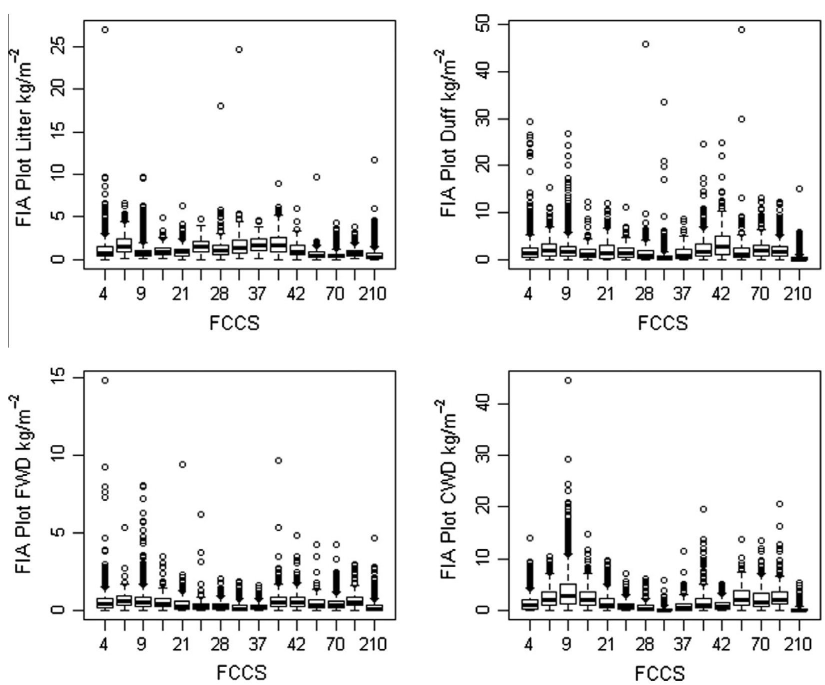

Fig. 4. The 12 most common FCCS classes keyed for each FIA plot compared to the measured fuel loading for the same plot for the four fuel components: (a) litter, (b) duff, (c) FWD and (d) CWD (see Table 1 for definitions of fuel components).

poorly with mapped FLM loadings (Table 7), with R^2 ranging from 0.04 to 0.17 and bias greater than 436% of the mean, and errors less than 22 kg m^{-2}.

4. Discussion

Results from this study demonstrate the remarkable difficulty in describing and mapping fuels for fire management. All three classifications performed poorly which resulted in poor map accuracies. The FLM classification appeared to perform better than both FCCS and FTG classifications probably because of the reliable differentiation and agreement for duff and CWD loadings, likely because these two components explain more of the variation in the FLM key than litter or FWD (Lutes et al., 2009). We found a high degree of redundancy in FWD and litter fuel loadings across most classes in all classification systems (Figs. 3–5) and this redundancy

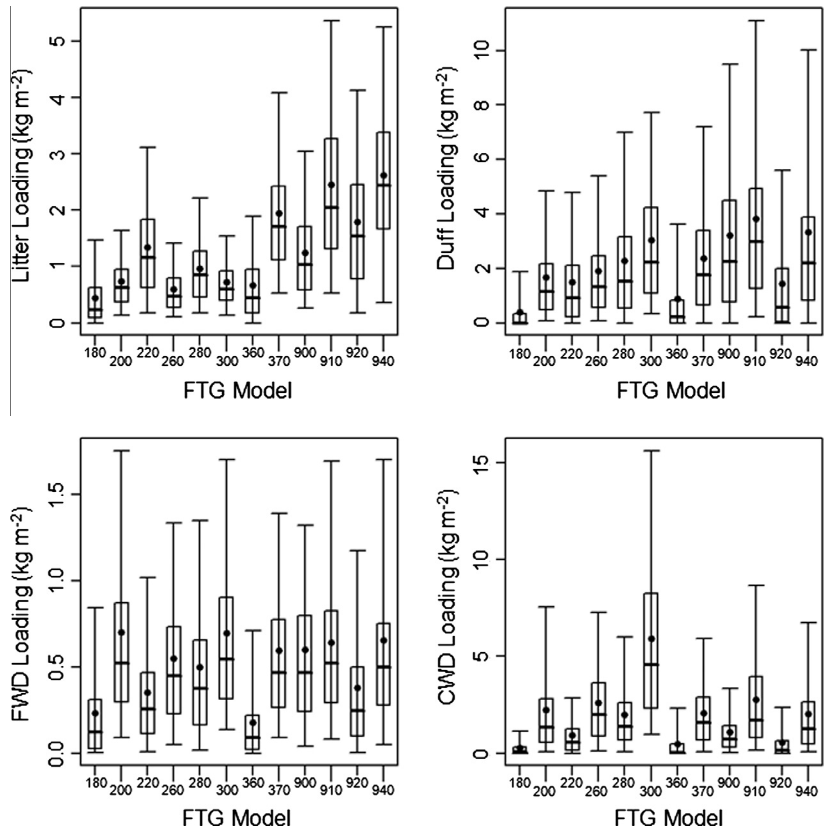

Fig. 5. The 12 most common FTG classes keyed for each FIA plot compared to the measured fuel loading for the same plot for the four fuel components: (a) litter, (b) duff, (c) FWD and (d) CWD (see Table 1 for definitions of fuel components).

Table 4
Comparison of the **FIA-keyed classification** class loadings for the three fuel classifications to the reference FIA-measured surface fuel component loadings using regression and error statistics. Ideally, R^2 and slopes should be close to 1.0, intercepts should be zero, % bias should be zero, and Root Mean Square Error (RMSE) should be zero. Surface fuels are described in Table 1.

Classification	Reference	Sample Size	Fuel Component	R^2	Slope	Intercept	% Bias	RMSE
Fuel Loading Models (FLM)								
FLM	FIA	13,138	Duff	0.84	1.02	0.04	4.9	1.01
			Litter	0.20	0.88	0.65	147.6	1.15
			FWD	0.16	0.62	0.16	−4.2	0.55
			CWD	0.70	0.98	0.48	40.3	1.38
			TSFL	0.77	1.00	1.12	31.0	2.45
Fuel Characteristics Classification System (FCCS)								
FCCS	FIA	10,471	Duff	0.02	0.03	1.37	−86.4	16.30
			Litter	0.04	0.24	0.71	−28.8	1.34
			FWD	0.07	0.08	0.21	−86.7	3.74
			CWD	0.11	0.12	1.02	−71.8	7.91
			TSFL	0.14	0.09	2.82	−79.3	25.77
Fuel Type Groups (FTG)								
FTG	FIA	10,472	Duff	0.27	0.27	0.74	0.06	0.92
			Litter	0.10	0.10	1.51	0.01	2.39
			FWD	0.10	0.10	0.44	0.26	0.54
			CWD	0.25	0.25	1.25	0.09	2.07
			TSFL	0.23	0.23	3.70	0.07	3.91
FLM vs FCCS								
FLM	FCCS	10,471	Duff	0.02	0.03	1.32	−87.0	1.32
			Litter	0.02	0.09	0.31	−70.7	1.45
			FWD	0.16	0.08	0.24	−85.9	3.69
			CWD	0.10	0.10	0.69	−79.6	8.25
			TSFL	0.13	0.08	1.95	−84	26.75

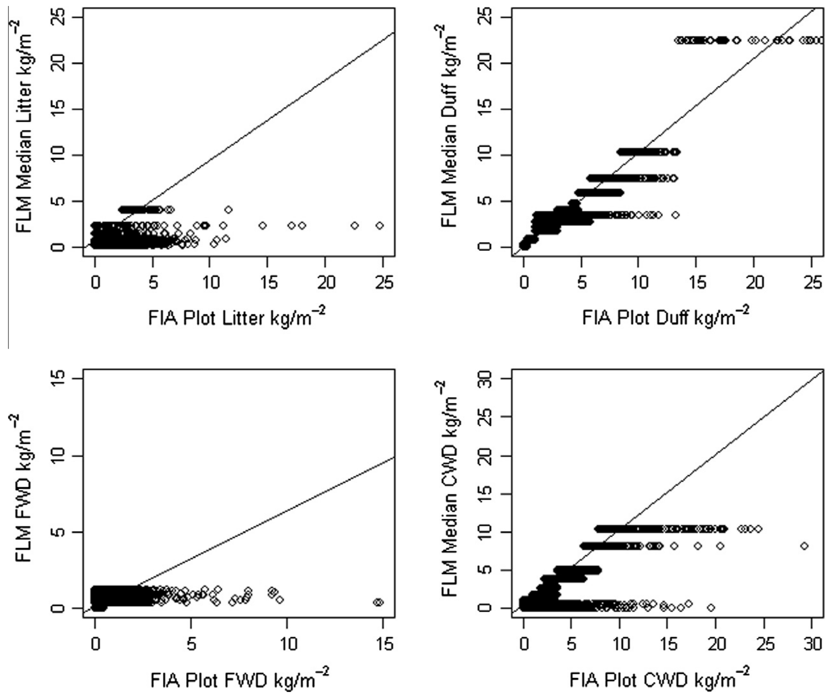

Fig. 6. Relationships of measured FIA loadings to the keyed FLM median fuel loadings for FIA plots for the following fuel components (a) litter, (b) duff, (c) FWD and (d) CWD (see Table 1 for definitions of fuel components).

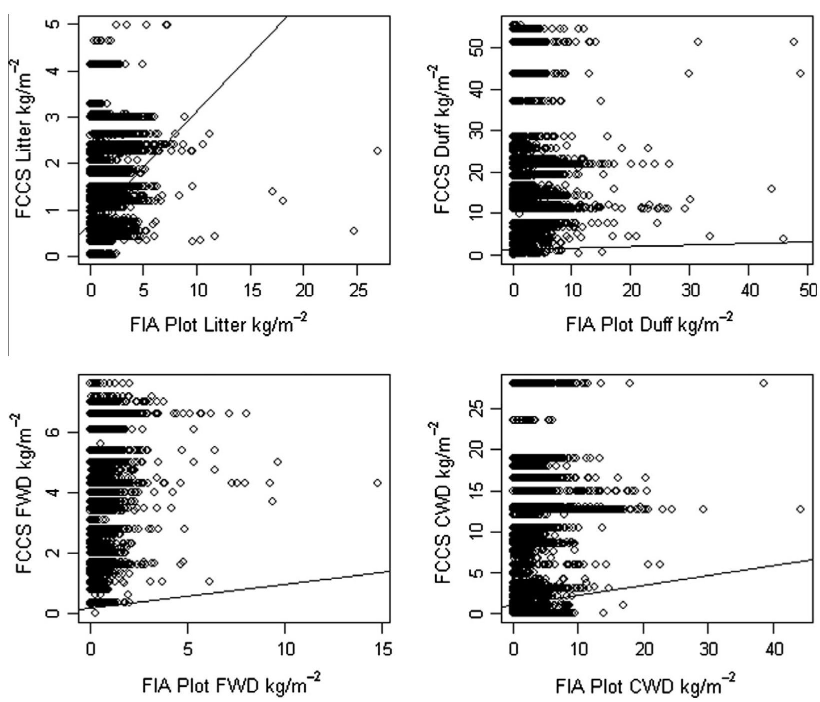

Fig. 7. Relationships of measured FIA loadings to the keyed FCCS fuel loadings for the following fuel components (a) litter, (b) duff, (c) FWD and (d) CWD (see Table 1 for definitions of fuel components).

probably served to make accurate quantification of classification fuel loadings difficult (Table 4 and Figs. 6–8). Poor classification performances for loadings (Table 4) are the major reason why the map layers have poor accuracies (FLM 25%, FCCS 34%, and FTG 64%) and poor loading comparisons (Table 7). It is nearly impossible to accurately map fuel loadings when the classifications cannot effectively discriminate fuel component loadings within classification classes. Even when we summed all component loadings into a total surface fuel load (TSFL), we got poor classification performances for FCCS and FTG (Table 4) and poor mapping accuracies (Table 7), indicating that the problem is not because the loading was inappropriately stratified.

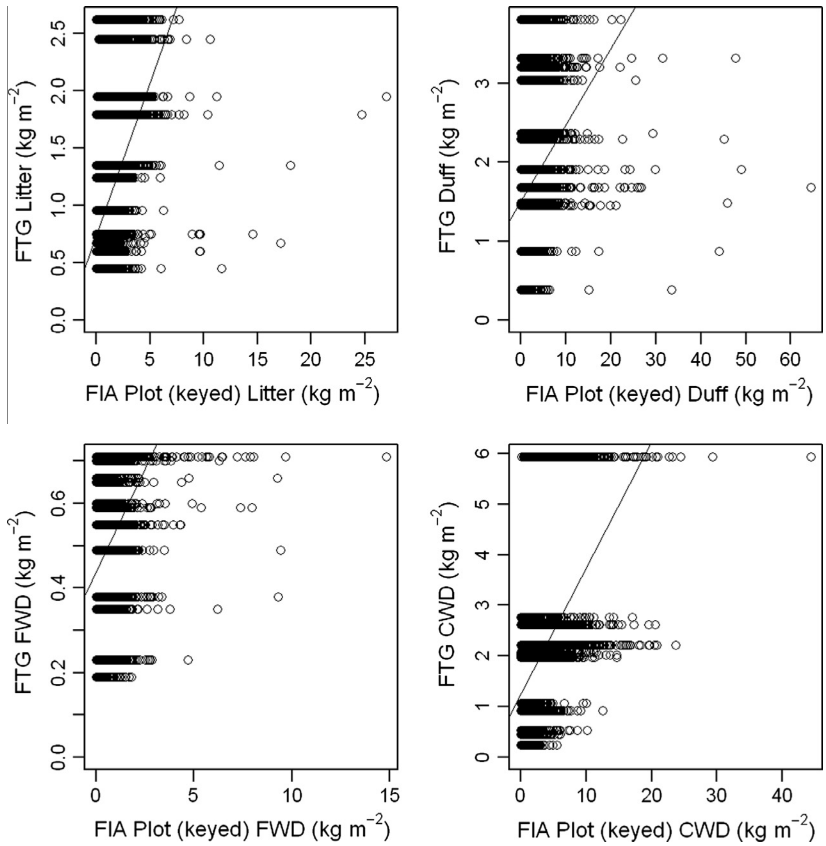

Fig. 8. Relationships of measured FIA loadings to the keyed FTG fuel loadings for the following fuel components (a) litter, (b) duff, (c) FWD and (d) CWD (see Table 1 for definitions of fuel components).

Table 5
Regression and error statistics for the comparison of PM2.5 emissions for the fuel loadings of keyed fuel classifications versus PM2.5 emissions based on the measured FIA loadings. Ideally, R^2 and slopes should be close to 1.0, intercepts should be zero, % bias should be zero, and Root Mean Square Error (RMSE) should be zero. FLM-Fuel Loading Models, FCCS-Fuel Characteristics Classification System, FTG-Fuel Type Groups.

Classification	R^2	Slope	Intercept	% Bias	RMSE
FLM	0.74	0.732	28.1	−24.2	534.4
FCCS	0.12	0.370	1070.0	43.5	1198.0
FTG	0.21	0.210	740.2	−5.6	837.7

Probably the most important reason why these classifications performed so poorly was the high degree of variability in fuel loading in each of the four fuel components and the interaction of this variability across spatial scales, which complicates sampling, mapping, and classification (Keane et al., 2012a). The fuel classifications of FLMs, FCCSs, and FTGs best describe fuel information for small areas so their accuracies will always be low unless they are applied at the finest scale of variability (probably 1–5 m patch sizes), which is often too small for cost-effective fuel sampling and mapping. In other words, FLM, FCCS, and FTG description systems assessments are point estimates so when their application is across large spatial scales (pixel or stand), there is a higher chance that multiple classes will occur because of high spatial variability that acts at different scales for each fuel component (i.e., the variability within a pixel was so great that it overwhelmed the comparison making it difficult to assess classification accuracy). This is especially true in managed stands where slash piles, thinning techniques, and harvest methods dictate spatial variability and distribution (Domke et al., 2013; Keane et al., 2012b). Moreover, there is also a high variability and uncertainty in the FIA estimates and methods used to collect fuels. Westfall and Woodall (2007) found that 15 of 27 fuel variables assessed on FIA plots did not attain the desired repeatability levels and some components (duff, litter and CWD) may have potential measurement bias. And the ancillary data needed for that calculation of loading for some components (e.g., litter and duff bulk densities, wood particle densities) are often lacking in many western US ecosystems (Woodall et al., 2012). An alternative analysis for this study would have been to use each FIA planar intercept transect as a sampling unit and compute fuel component loading means and deviations across all transects on individual FIA plots. We could then compare the FIA mean and variation to the mean and variation of the data within the keyed FLM category and the mean and variation of the data used to create the keyed FTG fuelbed. However, these data were not available to us and there are no measures of loading variability within FCCS classes without obtaining the original plot data. Another related scale issue is that the footprint of the FIA plot (6000 m^2) is an imperfect match to the LANDFIRE pixels (900 m^2) and RSAC forest type group pixel (62,500 m^2).

The top–down FLM classification showed the most promising results even though our comparison also showed a great deal of uncertainty. FLMs had good classification performance for duff and CWD but poor differentiation of FWD and litter loading (Table 4 and Fig. 3). The primary reason for the low FWD and litter correlation is because the FLMs were developed for identifying fuelbeds with significantly different PM2.5 emissions and soil surface temperature. By their nature, each FLM class represents a wide range of FWD and litter loading with similar emissions and surface

Table 6
Contingency table showing the accuracy of the LANDFIRE FLM map by comparing the mapped modal FLM value for the FIA plot location with the FLM value keyed from the FIA measured fuel loading data for that location. The shaded cells in the table are the number of plots that were correctly identified using the FIA plots.

FLM		Predicted-LANDFIRE mapped FLM																				Omission error (%)
Observed-FLM Keyed from FIA plot		11	12	13	21	31	41	51	61	62	63	64	71	72	81	83	91	92	93	101	102	
	11	2008	83	62	224	391	3	3	6	3	5	31	32	61	6	46	4	37	1	9	1	33
	12	91	7	4	9	22	0	0	0	0	0	5	0	2	4	1	2	3	0	1	0	95
	13	137	16	38	49	76	0	1	5	0	4	7	12	19	7	28	2	26	0	10	0	91
	21	809	60	68	250	391	4	3	9	0	4	14	31	61	7	82	8	38	0	8	0	86
	31	749	80	83	229	414	5	2	19	2	8	10	66	48	8	79	3	39	0	12	0	78
	41	111	5	5	17	28	0	0	3	0	0	7	0	3	1	3	0	4	0	1	1	100
	51	21	3	3	13	21	0	1	2	0	0	1	4	2	0	2	0	1	0	1	0	99
	61	106	29	38	67	77	1	3	13	0	3	7	22	14	4	42	0	38	0	15	0	97
	62	2	2	0	2	3	0	0	0	0	0	0	1	0	0	0	0	0	0	0	0	100
	63	21	9	12	16	19	1	0	3	0	1	0	10	6	0	10	0	5	0	1	0	99
	64	142	29	23	74	112	1	0	4	0	3	8	26	22	4	27	0	16	0	2	0	98
	71	207	51	56	87	143	6	0	9	1	3	9	27	34	5	44	4	39	1	11	3	96
	72	209	18	21	85	142	2	1	4	0	3	3	24	19	2	31	0	21	0	3	0	97
	81	15	14	6	13	8	0	0	2	0	0	3	4	1	5	16	0	12	0	10	0	95
	83	178	46	68	108	110	2	1	13	0	5	8	27	26	15	71	4	50	0	22	0	91
	91	24	3	4	16	23	0	1	1	0	0	2	3	6	1	7	0	2	0	2	0	98
	92	21	31	27	24	19	0	1	8	0	0	1	6	5	6	34	2	47	0	14	0	91
	93	29	12	14	15	19	0	0	3	0	0	0	4	2	1	21	0	15	1	2	0	99
	101	13	5	5	8	12	0	0	1	0	0	0	0	1	0	7	0	6	0	6	0	91
	102	89	11	10	25	47	0	0	0	0	0	1	5	3	1	16	2	6	0	0	0	100
Commission error (%)		60	99	93	81	80	100	94	88	100	97	50	91	94	94	87	100	88	67	95	100	Overall Agree 25

Table 7
Comparison of the **mapped** classification class loadings for the three fuel classifications to the reference FIA-measured surface fuel component loadings using regression and error statistics. Ideally, R^2 and slopes should be close to 1.0, intercepts should be zero, % bias should be zero, and Root Mean Square Error (RMSE) should be zero. Surface fuels are described in Table 1.

Classification	Reference	Sample Size	Fuel Component	R^2	Slope	Intercept	% Bias	RMSE
Fuel Loading Models (FLM)								
FLM	FIA	11,740	Duff	0.01	0.11	1.62	−32.7	3.53
			Litter	0.01	0.25	0.97	−73.1	1.36
			FWD	0.03	0.27	0.39	18.0	0.66
			CWD	0.07	0.29	1.46	−45.7	2.96
			TSFL	0.08	0.30	4.19	−44.2	5.79
Fuel Characteristics Classification System (FCCS)								
FCCS	FIA	10,469	Duff	0.03	0.02	1.42	811.4	22.54
			Litter	0.02	0.15	0.85	39.8	1.46
			FWD	0.04	0.05	0.33	612.1	3.80
			CWD	0.12	0.08	1.10	356.7	11.40
			TSFL	0.13	0.06	3.39	474.8	35.51
Fuel Type Groups (FTG)								
FTG	FIA	10,470	Duff	0.17	0.20	0.78	−3.52	0.98
			Litter	0.07	0.08	1.58	−2.39	2.42
			FWD	0.06	0.08	0.47	0.89	0.55
			CWD	0.18	0.20	1.44	−0.07	2.21
			TSFL	0.17	0.19	4.05	−1.47	4.07
FLM vs FCCS								
FLM	FCCS	11,738	Duff	0.04	1.28	14.50	1259.1	22.43
			Litter	0.04	0.64	1.34	436.1	1.59
			FWD	0.04	0.05	0.33	781.5	3.80
			CWD	0.11	1.47	6.70	757.4	11.84
			TSFL	0.17	2.56	21.96	939.2	36.35

soil temp. Another source of error was the assumption that median fuel load of the assigned FLM class accurately represented loadings for FWD and litter. Given the large number of zero and low values, another central tendency statistic might have been better. FLMs performed quite well for predicting PM2.5 smoke emissions (R^2 = 0.74; Table 5) and this is a direct result of the approach used in classification development where classes were clustered based on emissions and soil heating (Lutes et al., 2009).

Design mismatches between LANDFIRE mapping and the FCCS classification are probably the primary reason for the low FCCS LANDFIRE map accuracies. The FCCS fuelbeds were not designed to accommodate mapping across broad and diverse land areas; FCCS was designed for stand- or point-level on-site fuel description (Ottmar et al., 2007). Therefore it is difficult to scale this classification across large spatial domains. The LANDFIRE FCCS fuel map was created by representing broad vegetation types mapped by

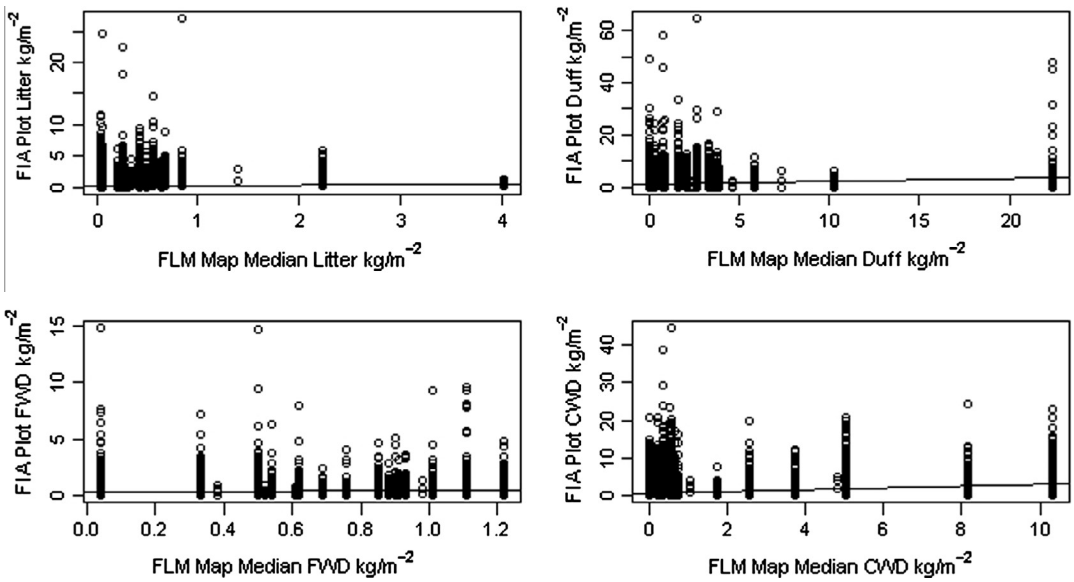

Fig. 9. Relationships of measured FIA loadings to the LANDFIRE mapped FLM median fuel loadings (Table 2) for FIA plots for the following fuel components (a) litter, (b) duff, (c) FWD and (d) CWD (see Table 1 for definitions of fuel components).

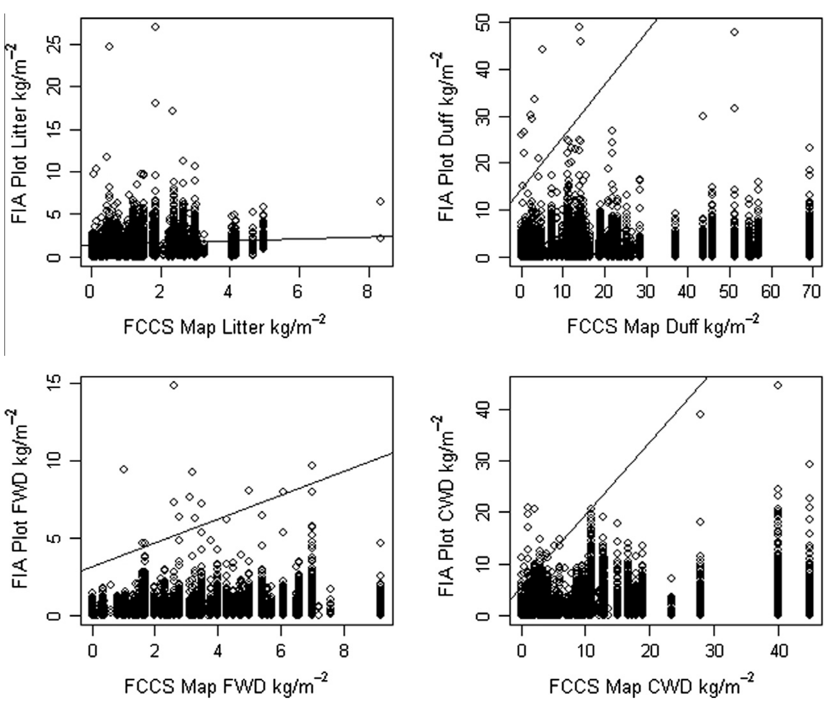

Fig. 10. Relationships of measured FIA loadings to the LANDFIRE mapped FCCS fuel loadings for the following fuel components (a) litter, (b) duff, (c) FWD and (d) CWD (see Table 1 for definitions of fuel components).

satellite imagery with a standard generic FCCS fuelbed that was created for finer scale applications. For site-specific applications, fire and fuels managers would need to customize these generic fuelbeds by adjusting loadings using local data.

FLM and FCCS mapping accuracies for the LANDFIRE refresh 2008 products are low partly because the LANDFIRE project did not have sufficient field data available at that time to build comprehensive FLM and FCCS maps and to conduct a thorough accuracy assessment. There were few national programs that gathered comprehensive fuel loading data, even though these fuel data are critical for carbon inventories, fire management, and wildlife habitat analysis. Therefore, instead of linking fuel classifications to biophysical settings, LANDFIRE had to link FLM and FCCS classes to vegetation attributes. We know of no other study that validated FLM or FCCS maps, but there have been studies that evaluated other fuel maps. Huang et al. (2009) created a map of coarse woody debris loading from a fusion of radar and optical remote sensing data and calculated an R^2 of 0.54 and a MAE of 2.9 kg m^{-2}. Brandis and Jacobson (2003) estimated vegetation fuel loads in Australia using Landsat TM imagery and computed R^2 that ranged from 0.01 to 0.79 when compared with field data. Keane et al. (1998) estimated that maps of Anderson (1982) fuel models for the Selway Bitterroot Wilderness Area ranged from 10% to 44% accurate. These results compare well with our study

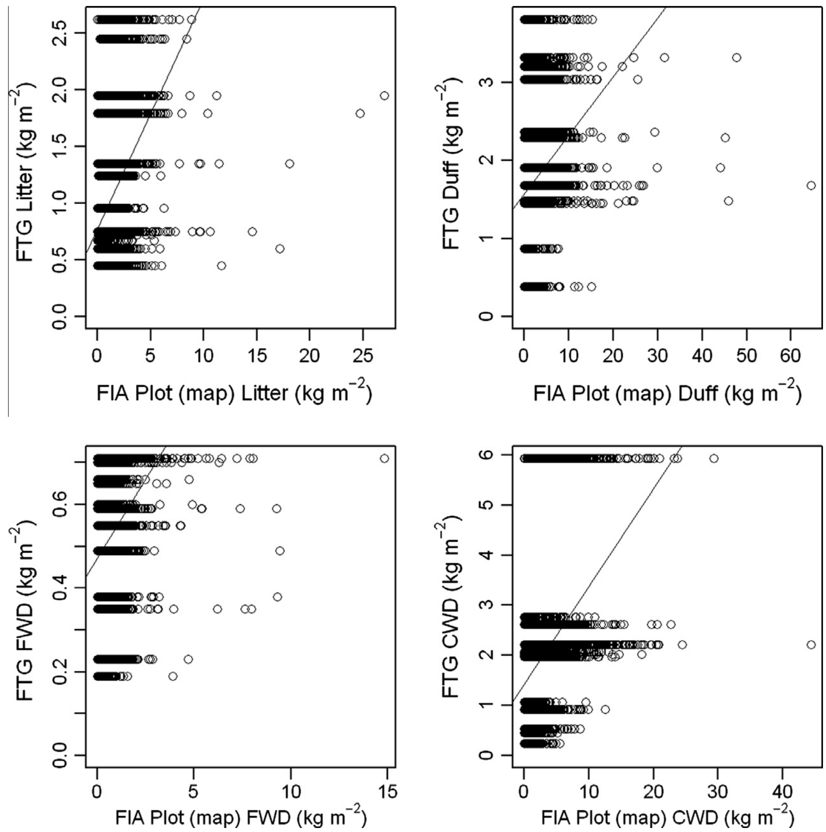

Fig. 11. Relationships of measured FIA loadings to the RSAC FTG mapped FTG fuel loadings (Table 3) for the following fuel components (a) litter, (b) duff, (c) FWD and (d) CWD (see Table 1 for definitions of fuel components).

in that all of them show that accurately mapping fuels is extremely difficult.

There are two ways to improve these classifications. The easiest and quickest is to expand the scope and context of the current classifications to increase accuracies. We suggest that the FLM classification be redone with the new FIA fuels data, along with any other recently available fuel data sets, to refine current classes, add more classes, and improve key criteria (Lutes et al., 2009). Improving the FCCS classification would involve sampling many more fuelbeds to account for the diversity of fuel conditions across the US and then refining the key criteria used to select and map FCCS fuelbeds to focus more on the fuelbed than the vegetation. FTG performance could be improved by (1) summarizing the fuels data over FIA forest types instead of groups, (2) including non-forest types, and (3) stratifying the summary of FIA loading of forest type classes by region, physiographic setting, and ownership. However, we feel that these suggested improvements may result in only minor to moderate increases in accuracy. The harder and more effective way to improve these classifications is to incorporate the high variability and scale of fuels, along with those processes that control fuel dynamics, into the classification (Keane, 2013). This would require extensive basic research to understand fuel dynamics, explore interactions between vegetation, disturbance, and biophysical processes, and identify those processes that influence fuel attributes (Keane, 2013). Then, fuel properties can be linked to those biophysical gradients that can be mapped and used in conjunction with appropriately scaled remote sensing products to map fuel loadings.

4.1. Management implications

Although mapping and loading accuracies for the three classifications were low, we feel that the three fuel classifications and the LANDFIRE maps are still quite useful to most fire management applications, especially across broad scales, because they (1) depict relative differences in fuel loadings across major regions, (2) represent state-of-the-art fuel mapping technology, and (3) are the only spatial surface fuel resource available at this time. Users of this technology should account for the high uncertainty of these classifications found in this study when designing their analyses and interpreting their results. The use of FLMs for smoke emissions, for example, has a lower uncertainty than using FLMs for carbon inventories. The poor performances and low mapping accuracies indicate a real scale issue with the current fuel classifications and their associated maps in that the high variability of fuel loadings acting across multiple scales make accurate mapping of fuel loadings with current classifications difficult.

One possible simple method to incorporate the inherent uncertainty of fuel loading estimates into fire management applications is to use the bias and RMSE estimates quantified in this study (Tables 4 and 7) as bounds on classification loadings. Fuel loadings for a fuel classification class can be made into a range by adding the RMSE or incorporating the percent bias into the loading number. For example, the range of the median duff loading for FLM 051 of 3.55 kg m^{-2} (Table 2) can be approximated to 2.54 to 4.56 kg m^{-2} using the RMSE of 1.01 (Table 4). Then, the summed lower and upper ranges of the estimates can be input into models such as FOFEM to simulate a range of possible effects.

Other more intensive approaches to incorporate variability into fuel products may be to include an expression of uncertainty in the estimate. An additional map layer, for example, might describe the level of variability associated with using the mean or median loadings for pixel's assigned classification category based on findings from this study. This variability would be quantified from the base data used to develop the classification. Or, the map may describe the spatial structure of the variability; Keane et al. (2012a), for example, proposed mapping the parameters of algorithms used to simulate the spatial distribution of surface fuel component loading. Fuel classifications could be modified to identify redundancies in loading between classes for each component with a detailed quantification of the variability of loading for each component by class.

Acknowledgements

We thank the USDA Forest Inventory and Analysis program, the LANDFIRE project, and the National Fire Plan for project support, data, and funding. Portions of this work were performed under the terms of an interagency agreement between the LANDFIRE program and the USDA Forest Service Forest Inventory and Analysis program in support of fuel load mapping in LANDFIRE. We also thank Allissa Corrow for initial analyses and technical help; Don Long and Matt Reeves, US Forest Service Rocky Mountain Research Station, for technical review.

References

Albini, F.A., 1976. Estimating wildfire behavior and effects. USDA Forest Service Intermountain Research Station, Ogden, UT, General Technical, Report INT-30. pp. 23.

Anderson, H.E., 1982. Aids to determining fuel models for estimating fire behavior. USDA Forest Service Intermountain Research Station, Ogden, Utah, USA, General Technical Report INT-122. 22 p.

Arner, S.L., Woudenberg, S., Waters, S., Vissage, J., MacLean, C., Thompson, M., Hansen, M., 2003. National algorithms for determining stocking class, stand size class, and forest type for Forest Inventory and Analysis plots, US Department of Agriculture Forest Inventory and Analysis, Washington, D.C., 65p.

Arroyo, L.A., Pascual, C., Manzanera, J.A., 2008. Fire models and methods to map fuel types: the role of remote sensing. Forest Ecology and Management 256, 1239–1252.

Bechtold, W.A., Patterson, P.L. (Eds.) 2005. The enhanced Forest Inventory and Analysis program—national sampling design and estimation procedures. USDA Forest Service Southern Research Station, Asheville, North Carolina, USA, General Technical, Report SRS-80. pp. 34.

Berg, E., 2007. Characterizing and classifying complex fuels — a new approach. Canadian Journal of Forest Research 37, 2381–2382.

Brandis, K., Jacobson, C., 2003. Estimation of vegetative fuel loads using Landsat TM imagery in New South Wales, Australia. International Journal of Wildland Fire 12, 185–194.

Brown, J.K., 1974. Handbook for inventorying downed woody material. In: USDA Forest Service, Intermountain Forest and Range Experiment Station, Ogden, UT, USA, pp. 34.

Brown, J.K., Bevins, C.D., 1986. Surface fuel loadings and predicted fire behavior for vegetation types in the northern Rocky Mountains. In: US Department of Agriculture, Forest Service, Intermountain Forest and Range Experiment Station, Ogden, UT USA, pp. 9.

Burgan, R.E., 1987. Concepts and interpreted examples in advanced fuel modeling. In: USDA Forest Service, pp. 40.

de Groot, W.J., Landry, R., Kurz, W.A., Anderson, K.R., Englefield, P., Fraser, R.H., Hall, R.J., Banfield, E., Raymond, D.A., Decker, V., Lynham, T.J., Pritchard, J.M., 2007. Estimating direct carbon emissions from Canadian wildland fires1. International Journal of Wildland Fire 16, 593–606.

Deeming, J.E., Burgan, R.E., Cohen, J.D., 1977. The National Fire Danger Rating System – 1978. USDA Forest Service Intermountain Forest and Range Experiment Station, Ogden, Utah, General Technical, Report INT-39. pp. 63.

Domke, G.M., Woodall, C.W., Walters, B.F., Smith, J.E., 2013. From models to measurements: comparing downed dead wood carbon stock estimates in the US Forest Inventory. PLoS One 8, e59949.

Harmon, M.E., Franklin, J.F., Swanson, F.J., Sollins, P., Gregory, S.V., Lattin, J.D., Anderson, N.H., Cline, S.P., Aumen, N.G., Sedell, J.R., Lienkaemper, G.W., Cromack, K., Cummins, K.W., 1986. Ecology of coarse woody debris in temperate ecosystems. Advances in Ecological Research 15, 133–302.

Harmon, M.E., Woodall, C.W., Fasth, B., Sexton, J., 2008. Woody detritus density and density reduction factors for tree species in the United States: A synthesis. In: USDA Forest Service Northern Research Station, Newton Square, PA USA, General Technical, Report NRS-29. pp. 84.

Huang, S., Crabtree, R.L., Potter, C., Gross, P., 2009. Estimating the quantity and quality of coarse woody debris in Yellowstone post-fire forest ecosystem from fusion of SAR and optical data. Remote Sensing of Environment 113, 1926–1938.

JMP IN. 2003. JMP IN 5.1. SAS Institute: Cary, N.C. 434 pages.

Keane, R.E., 2013. Describing wildland surface fuel loading for fire management: a review of approaches, methods and systems. International Journal of Wildland Fire 22, 51–62.

Keane, R.E., Garner, J.L., Schmidt, K.M., Long, D.G., Menakis, J.P., Finney, M.A., 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, pp. 66.

Keane, R.E., Burgan, R.E., Wagtendonk, J.V., 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.

Keane, R.E., Rollins, M., Zhu, Z.L., 2007. Using simulated historical time series to prioritize fuel treatments on landscapes across the United States: the LANDFIRE prototype project. Ecological Modelling 204, 485–502.

Keane, R., Gray, K., Bacciu, V., Leirfallom, S., 2012a. Spatial scaling of wildland fuels for six forest and rangeland ecosystems of the northern Rocky Mountains, USA. Landscape Ecology 27, 1213–1234.

Keane, R.E., Gray, K., Bacciu, V., 2012b. Spatial variability of wildland fuel characteristics in northern Rocky Mountain ecosystems. In: USDA Forest Service Rocky Mountain Research Station, Fort Collins, Colorado, pp. 56.

Krivtsov, V., Vigy, O., Legg, C., Curt, T., Rigolot, E., Lecomte, I., Jappiot, M., Lampin-Maillet, C., Fernandes, P., Pezzatti, G.B., 2009. Fuel modelling in terrestrial ecosystems: an overview in the context of the development of an object-orientated database for wild fire analysis. Ecological Modelling 220, 2915–2926.

Lutes, D.C., Keane, R.E., Caratti, J.F., Key, C.H., Benson, N.C., Sutherland, S., Gangi, L.J., 2006. FIREMON: Fire effects monitoring and inventory system. In. USDA Forest Service Rocky Mountain Research Station, Fort Collins, CO USA, p. 222.

Lutes, D.C., Keane, R.E., Caratti, J.F., 2006. A surface fuel classification for estimating fire effects. International Journal of Wildland Fire 18, 802–814.

McKenzie, D., Raymond, C.L., Kellogg, L., Norheim, R.A., Andreu, A.G., Bayard, A.C., Kopper, K.E., Elman, E., 2007. Mapping fuels at multiple scales: landscape application of the fuel characteristic classification system. Canadian Journal of Forest Research 37, 2421–2437.

McKenzie, D., French, N.H.F., Ottmar, R.D., 2012. National database for calculating fuel available to wildfires. Eos 93, 57–58.

MTBS, 2012. Monitoring trends in burn severity, Data Access: Burned Area Boundaries Data. <http://mtbs.gov/compositfire/mosaic/bin-release/burnedarea.html> (last access: 10.10.12).

Neary, D.G., Klopatek, C.C., DeBano, L.F., Ffolliott, P.F., 1999. Fire effects on belowground sustainability: a review and synthesis. Forest Ecology and Management 12, 51–57.

Ottmar, R.D., Sandberg, D.V., Riccardi, C.L., Prichard, S.J., 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.

Pyne, S.J., Andrews, P.L., Laven, R.D., 1996. Introduction to Wildland Fire. John Wiley & Sons, New York.

Reeves, M.C., Ryan, K.C., Rollins, M.C., Thompson, T.G., 2009. Spatial fuel data products of the LANDFIRE project. International Journal of Wildland Fire 18, 250–267.

Reinhardt E., Keane, R.E., Brown J.K., 1997. First order fire effects model: FOFEM 4.0 User's Guide. USDA Forest Service, General Technical Report INT-GTR-344. 33 pages.

Reynolds, K.M., Hessburg, P.F., Keane, R.E., Menakis, J.P., 2009. National fuel-treatment budgeting in US federal agencies: capturing opportunities for transparent decision-making. Forest Ecology and Management 258, 2373–2381.

Riccardi, C.L., Ottmar, R.D., Sandberg, D.V., Andreu, A., Elman, E., Kopper, K., Long, J., 2007a. The fuelbed: a key element of the fuel characteristic classification system. Canadian Journal of Forest Research 37, 2394–2412.

Riccardi, C.L., Prichard, S.J., Sandberg, D.V., Ottmar, R.D., 2007b. Quantifying physical characteristics of wildland fuels using the fuel characteristic classification system. Canadian Journal of Forest Research 37, 2413–2420.

Rollins, M.G., 2009. LANDFIRE: a nationally consistent vegetation, wildland fire, and fuel assessment. International Journal of Wildland Fire 18, 235–249.

Rothermel, R.C., 1972. A mathematical model for predicting fire spread in wildland fuels. United States Department of Agriculture, Forest Service, Intermountain Forest and Range Experiment Station, Report Research Paper INT-115, Ogden, Utah.

Ruefenacht, B., Finco, M.V., Nelson, M.D., Czaplewski, R., Helmer, E.H., Blackard, J.A., Holden, G.R., Lister, A.J., Salajanu, D., Weyermann, D., Winterberger, K., 2008. Conterminous US and Alaska forest type mapping using forest inventory and analysis data. Photogrammetric Engineering and Remote Sensing 74, 1379–1388.

Sandberg, D.V., Ottmar, R.D., Cushon, G.H., 2001. Characterizing fuels in the 21st century. International Journal of Wildland Fire 10, 381–387.

Sikkink, P., Keane, R.E., Lutes, D.C., 2009. Field guide for identifying fuel loading models. In: USDA Forest Service Rocky Mountain Research Station, Fort Collins, CO, USA, pp. 44.

Ucitel, D., Christian, D.P., Graham, J.M., 2003. Vole use of coarse woody debris and implications for habitat and fuel management. The Journal of Wildlife Management 67, 65–72.

Urbanski, S., Hao, W.M., Nordgren, B., 2011. The wildland fire emission inventory: western United States emission estimates and an evaluation of uncertainty. Atmospheric Chemistry and Physics 11, 12973–13000.

US Department of Agriculture, Forest Service. 2007. Forest Inventory and Analysis national core field guide, volume I: field, data collection procedures for phase 2 plots, version 4.0. Washington, DC: US Department of Agriculture Forest Service, Forest Inventory and Analysis, Washington, D.C.: <http://fia.fs.fed.us/library/field-guides-methods-proc/> (accessed 01.13).

Westfall, J.A., Woodall, C.W., 2007. Measurement repeatability of a large-scale inventory of forest fuels. Forest Ecology and Management 253, 171–176.

Woodall, C.W., Monleon, V.J., 2008. Sampling Protocol, Estimation, and Analysis Procedures for the Down Woody Materials Indicator of the FIA program. USDA Forest Service General Technical Report NRS-22, Newtown Square, PA, USA. 68 p.

Woodall, C.W., Monleon, V.J., 2010. Estimating the quadratic mean diameters of fine woody debris in forests of the United States. Forest Ecology and Management 260, 1088–1093.

Woodall, Christopher W.; Conkling, Barbara L.; Amacher, Michael C.; Coulston, John W.; Jovan, Sarah; Perry, Charles H.; Schulz, Beth; Smith, Gretchen C.; Will-Wolf, Susan. 2010. The Forest Inventory and Analysis Database Version 4.0: Database Description and Users Manual for Phase 3. Gen.Tech. Rep. NRS-61. Newtown Square, PA: U.S. Department of Agriculture, Forest Service, Northern Research Station. 180 p.

Woodall, C., Amacher, M., Bechtold, W., Coulston, J., Jovan, S., Perry, C., Randolph, K., Schulz, B., Smith, G., Tkacz, B., Will-Wolf, S., 2011. Status and future of the forest health indicators program of the USA. Environmental Monitoring and Assessment 177, 419–436.

Woodall, C.W., Perry, C.H., Westfall, J.A., 2012. An empirical assessment of forest floor carbon stock components across the United States. Forest Ecology and Management 269, 1–9.

Woudenberg, S.W., Conkling, B.L., O'Connell, B.M., LaPoint, E.B., Turner, J.A., Waddell, K.L., 2010. The Forest Inventory and Analysis Database: Database description and users manual version 4.0 for Phase 2. USDA Forest Service General Technical Report RMRS-GTR-245, Fort Collins, CO, USA. 339 p.