

Assessing Three Fuel Classification Systems and Their Maps Using Forest Inventory and Analysis (FIA) Surface Fuel Measurements

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Abstract—Fuel classifications are integral tools in fire management and planning because they are used as inputs to fire behavior and effects simulation models. Fuel Loading Models (FLMs) and Fuel Characteristic Classification System (FCCS) fuelbeds are the most popular classifications used throughout wildland fire science and management, 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.

Introduction

It is difficult and problematic for many managers to sample wildland fuels for a project area or wildfire so fuel classifications were created to simplify the input of fuelbed characteristics into the fire behavior and effects software packages used extensively in fire management (Burgan, 1987; Keane, 2013). Wildland fuels are the dead and live biomass available for fire ignition and combustion (Albini, 1976; Sandberg and others 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 and others 2008; Deeming and others 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 and others 1986; Pyne and others 1996). Fuel loads are required as

inputs to nearly all fire applications (Burgan, 1987; Krivtsov and others 2009), and they are also important for the quantification of carbon inventories (de Groot and others 2007), site productivity (Neary and others 1999), and wildlife habitat (Ucitel and others 2003).

Two fuel loading classifications are commonly used in fire management applications to predict fire effects such as smoke, soil heating, and tree mortality. Fuel Loading Models (FLMs) identify fuel classes designed specifically for predicting unique fire effects (Lutes and others 2009). The Fuel Characteristic Classification System (FCCS) (Ottmar and others 2007; Riccardi and others 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 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 and others 2008). Each of these classifications is different in that they were built using uniquely different approaches (Keane 2012). None of these classifications have been formally tested for performance and accuracy.

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Table 1—Descriptions of commonly used surface fuel components.

General Fuel Type	Fuel Component	Common Name	Size	Description
Downed Dead Woody	1 hour woody	Twigs	<1 cm (0.25 inch) diameter	Detached small woody fuel particles on the ground
	10 hour woody	Branches	1-2.5 cm (0.25-1.0 inch) diameter	Detached small woody fuel particles on the ground
	100 hour woody	Large Branches	2.5-7.6 cm (1-3 inch) diameter	Detached small woody fuel particles on the ground
	1000 hour 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, 100hr 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

Both 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 and others 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 and others 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 and others 2009). Yet, despite their widespread use, these three 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 and others 2009).

Recently, the Forest Inventory and Analysis (FIA) program 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 then 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 (see Keane and others 2013). 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.

FLMs

The FLMs of Lutes and others (2009) 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 (Keane and others 2013). 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 and others 2009). FLMs can be used as inventory techniques to quantify fuel characteristics (Sikkink and others 2009); as classifications of unique fuel types to facilitate communication between managers, scientists, and other professionals (Sandberg and others 2001); and, most importantly, as map units in fuel mapping efforts (Reeves and others 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 and others 2009).

FCCS

The FCCS uses a bottom-up approach for quantifying unique fuelbeds and associated fuelbed categories and subcategories (Ottmar and others 2007). In this flexible classification, fuelbeds are added into FCCS as they are identified and perhaps measured 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 and others 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 and others 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 and others 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. Moreover, FCCSs were developed to be used as map categories because of their fine scale application.

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 and others 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. We created the FTG classification by extracting the forest type group variable for each FIA plot (Arner and others 2003) and computing the mean loading for each fuel component for each forest type group using the keyed FIA fuels data. 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 and others 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 (FTGs) and it has been shown that fuels are rarely correlated to vegetation composition (Brown and Bevins, 1986; Keane and others 2012b).

Classification Maps

FLMs were mapped by the LANDFIRE project using the following protocol: (1) available FIA fuels plots were keyed to an FLM value using the Sikkink and others (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) an FLM class was systematically assigned to each pixel using a cross-walk approach where all possible pixels were assigned an FLM by vegetation type/cover/height hierarchical combinations. Because there were few data to assign an FLM to all combinations, pixels were assigned an FLM by using more general vegetation type/cover, or type/height combinations, and finally by a broad existing vegetation type group classification (Reeves and others 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 and others 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 and others 2009).

Scientists at the USDA Forest Service RSAC and FIA mapped forest type groups for the conterminous U.S. and Alaska with a spatial resolution of 250 m and an overall accuracy of 64% for the western U.S. (Ruefenacht and others 2008; <http://fsgeodata.fs.fed.us>). In the western conterminous U.S., 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 U.S. from 2003–2010 (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.

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 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 found a single pixel worked better than any average of surrounding pixels (Keane and others 2013). 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; particles 0-7.6 cm diameter), and coarse woody debris (CWD, particles 7.6+ cm diameter; also called logs or 1000 hr 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 weren't included in this study. We combined 1, 10, and 100 hr 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).

FIA Sampling and Data Compilation

The study area includes eight states in the western United States, covering the Pacific Northwest and Interior West FIA regions (Figure 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.

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 percent stocked with tree species, or land formerly having such tree cover and not currently developed for a non-forest use, at least 4,000 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 degrees, respectively, from the center of subplot 1 (USDA Forest Service 2007, Woodall and others 2010). 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 tree crown condition, soil conditions, lichen community composition, understory vegetation, and down woody material (Bechtold and Patterson, 2005; Woodall and Monleon, 2008; Woodall and others 2011).

Fuel sampling protocols are summarized in Keane and others (2012). 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

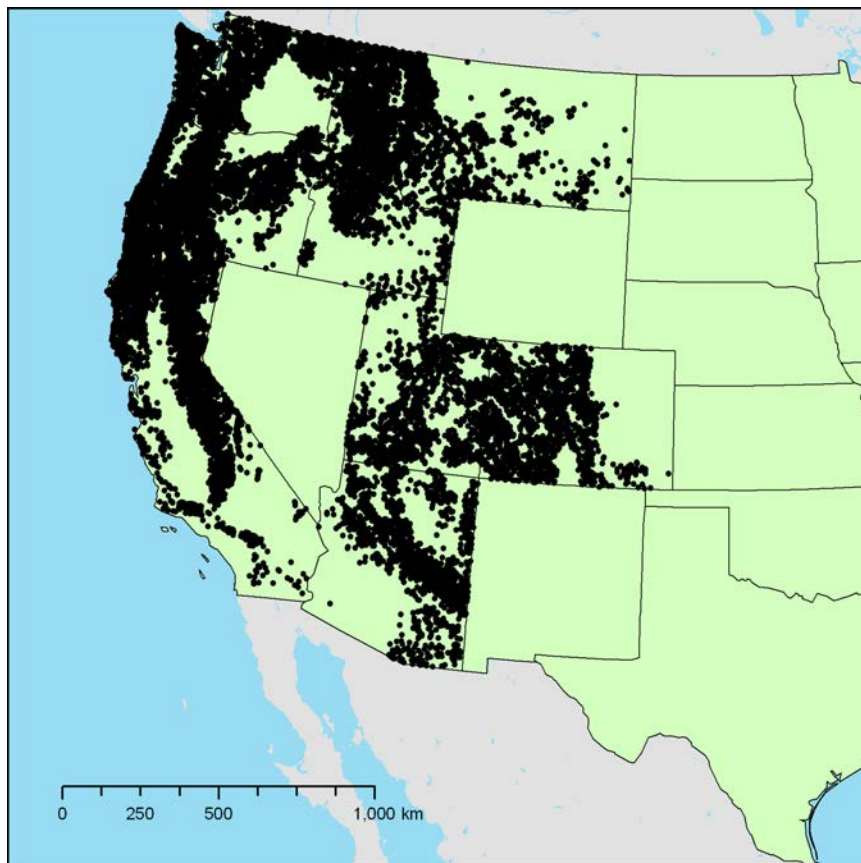


Figure 1—The approximate FIA plot locations for all plots used in this study.

and CWD, and systematic point sampling for duff and litter depths (Brown, 1974; Woodall and others 2010). Biomass estimates of CWD, FWD, litter, and duff were calculated using estimators detailed in Woodall and Monleon (2008).

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. 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 (Figure 1).

Keying Fuel Classification from FIA Data

The Sikkink and others (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.

LANDFIRE refresh mapping rule sets provided by Smail and others (2012) were used 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 2,667 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 Prichard and others (2012).

FTGs were already keyed to FIA plots based on the RSAC FIA forest type group classification (Arner and others 2003). Every FIA plot has an assigned FTG value and this value was matched to the FTG values (Keane and others 2013). 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

Analysis

To assess performance of FLM and FCCS classifications, we compared 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 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 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 to adjust for unequal observations in each mapped category. We analyzed the predictive power of the mapped values for the FIA values to represent loadings (how well are FIA data represented by the mapped fuel classification loadings) 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.

Results

Classification Performance

A 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 2; Figures 2-4). For FLMs, we found that FIA measured loadings compared well for duff and CWD with $R^2 > 0.70$ and slopes ranging from 0.98-1.02 (a slope of

Table 2—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	Fuel	R ²	Slope	Intercept	% Bias	RMSE
		Size	Component					
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

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 2; Figure 2). 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) (Figure 2).

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 2; Figures 3,4). All FCCS fuel component loadings were under-predicted with negative bias values greater than 28% of the mean, while bias for FTGs were significantly lower (0.01-0.26%) (Figure 3). 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 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% ($K_{\text{hat}} = 0.098$) of the time (Keane and others 2013). 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). The lightest load FLM 011 had both the highest agreement (67%) and highest number of plots (3,016), while the next most frequent FLMs (021, 031) had high plot numbers (1,847, 1,856 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.

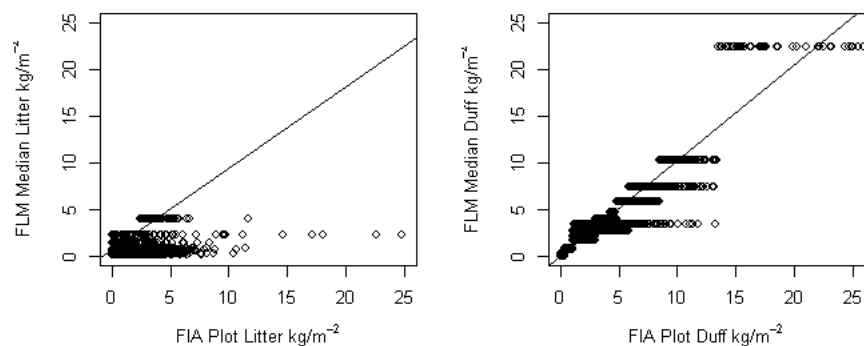


Figure 2—Relationships of measured FIA loadings to the keyed FLM median fuel loadings for FIA plots for the following fuel components (a) litter, (b) duff, (c) FWD, (d) CWD (see Table 1 for definitions of fuel components).

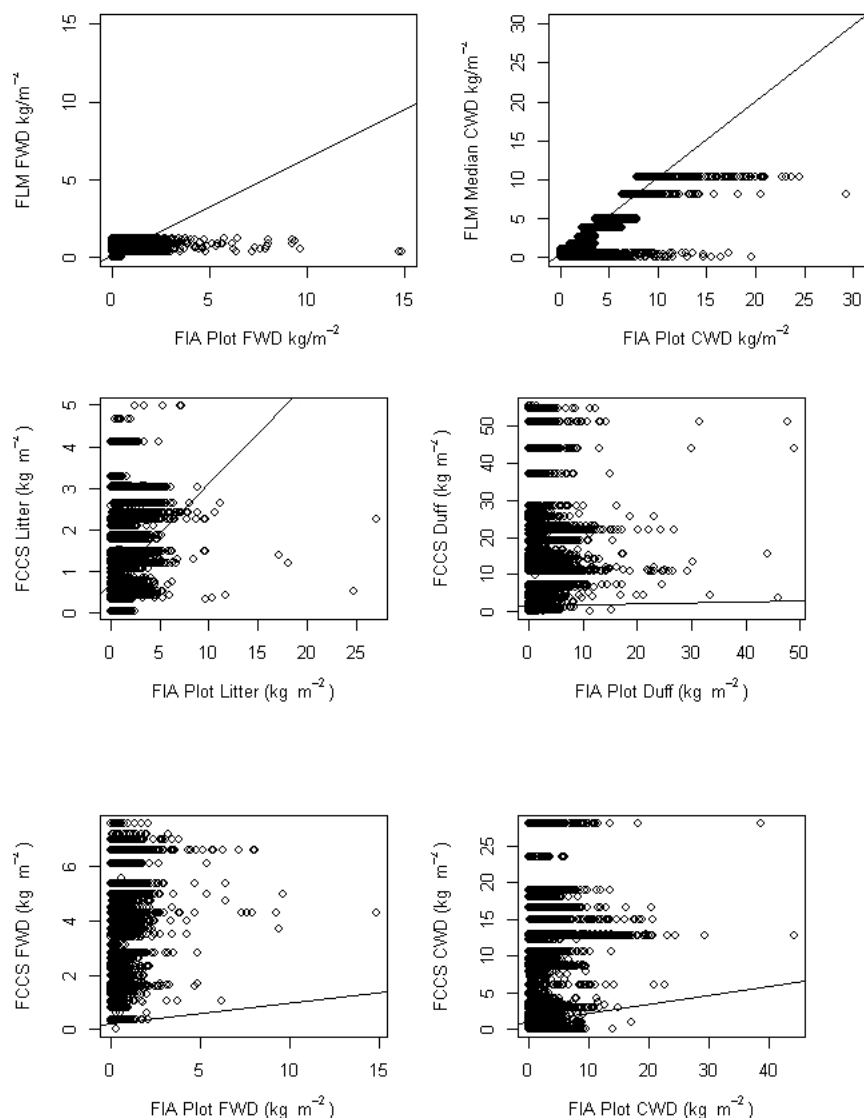


Figure 3—Relationships of measured FIA loadings to the keyed FCCS fuel loadings for the following fuel components (a) litter, (b) duff, (c) FWD, (d) CWD (see Table 1 for definitions of fuel components).

FCCS and FTG mapped class values compared better than mapped FLM classes to the FIA keyed classes (FCCS was 34% agreement, $K_{\text{hat}} = 0.33$ and FTG was 64% agreement, $K_{\text{hat}} = 0.54$). 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

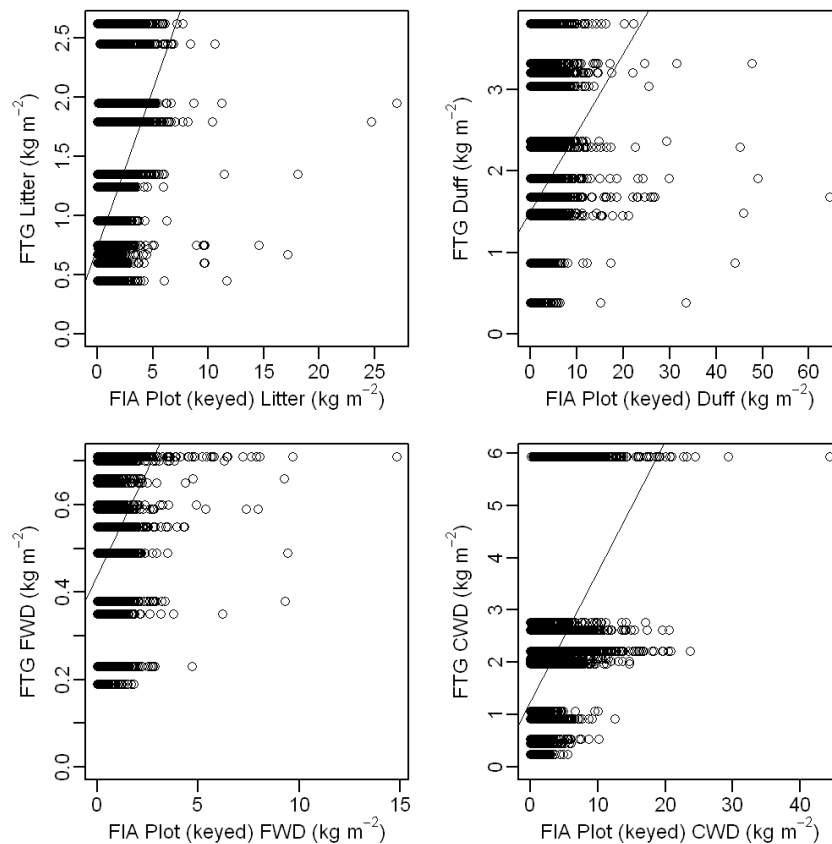


Figure 4—Relationships of measured FIA loadings to the keyed FTG fuel loadings for the following fuel components (a) litter, (b) duff, (c) FWD, (d) CWD (see Table 1 for definitions of fuel components).

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 3; Figures 5-7). 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) (Figure 5) and FTG components (< 0.20) (Figure 7), but are somewhat close to 1.0 for FCCS loadings (0.1-1.4) (Figure 6). 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 3). As expected, mapped FCCS fuelbed loadings compared poorly with mapped FLM loadings (Table 3), with R^2 ranging from 0.04-0.17 and bias greater than 436% of the mean, and errors less than 22 kg m^{-2} .

Discussion

Results from this study demonstrate the incredible difficulty in describing and mapping fuels for fire management (Keane 2013). 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 duff and CWD components explained more of the variation in the FLM key than litter or FWD (Lutes and others 2009). We found a high degree of redundancy in FWD and litter fuel loadings across most classes in all classification systems (Keane and others 2013) and this redundancy probably served to make accurate quantification of classification fuel loadings difficult (Table 2; Figures 2-7). Poor classification performances for loadings (Table 2) are the major reason why the map layers have poor accuracies (FLM 25%, FCCS 34%, and FTG 64%) and poor loading comparisons. It is nearly impossible to accurately map fuel loadings when the classifications can't 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 2) and poor mapping accuracies (Table 3), indicating that the problem is not because the loading was inappropriately stratified or summarized.

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 and others 2012a). The fuel classifications of FLMs, FCCSs, and FTGs best describe fuel information for small areas (a point; $< 5 \text{ m}^2$) so their accuracies will always be low unless they are applied at the finest scale of variability (probably

Table 3—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	Fuel	R²	Slope	Intercept	% Bias	RMSE
		Size	Component					
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

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 and others 2013; Keane and others 2012b).

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 2; Figure 2). The primary reason for the low FWD and litter correlation is because the FLMs were

developed for identifying fuelbeds with significantly different PM_{2.5} 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 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.

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 and others 2001). 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 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

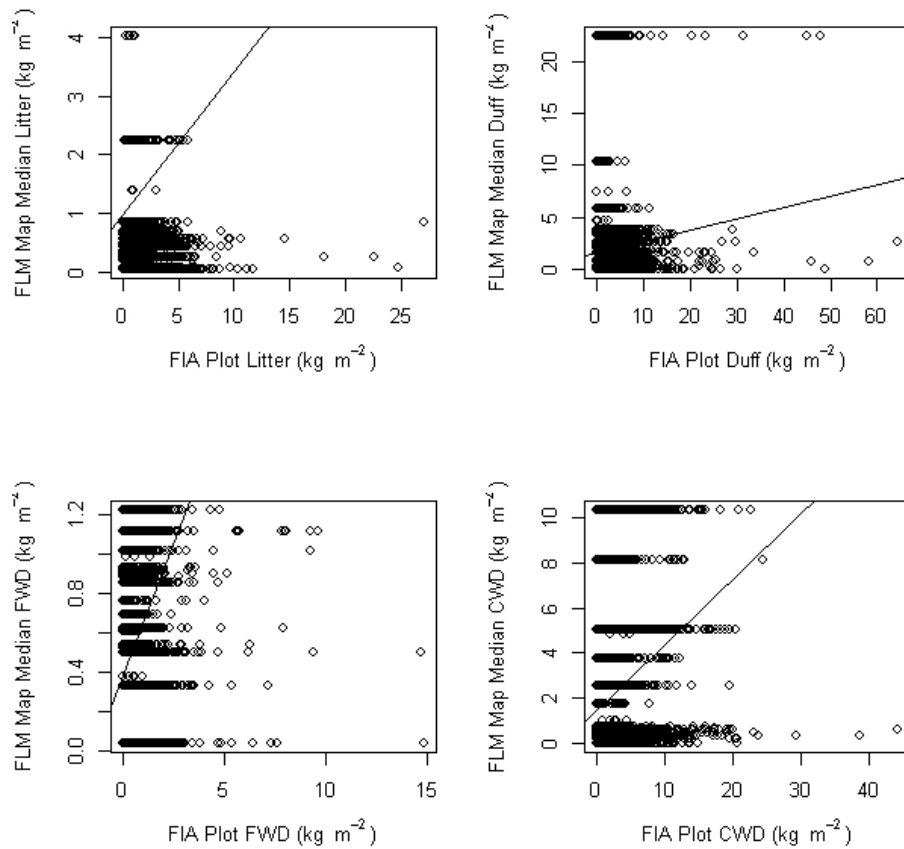


Figure 5—Relationships of measured FIA loadings to the LANDFIRE mapped FLM median fuel loadings (Table 2) for FIA plots for the following fuel components (a) litter, (b) duff, (c) FWD, (d) CWD (see Table 1 for definitions of fuel components)

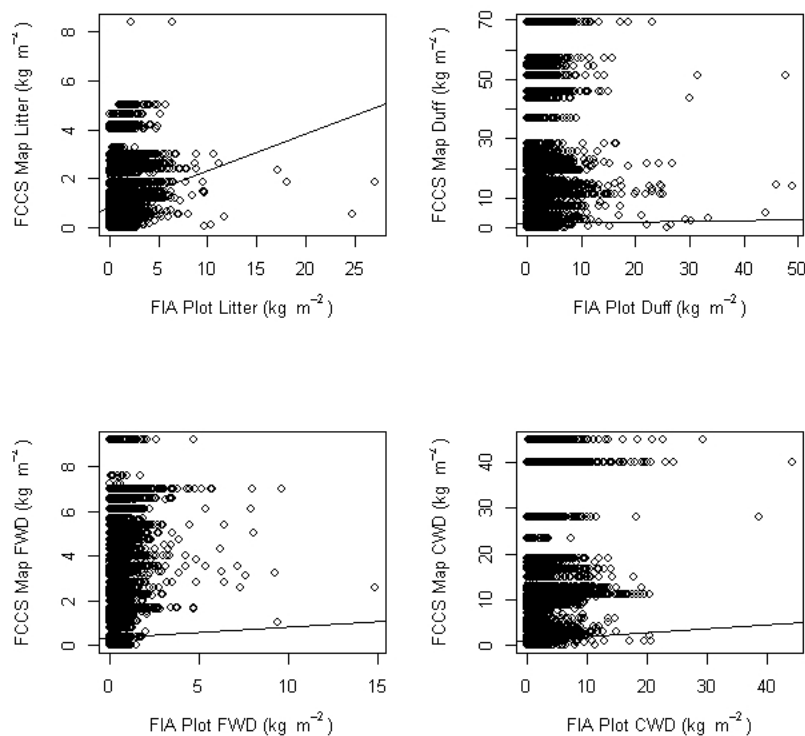


Figure 6—Relationships of measured FIA loadings to the LANDFIRE mapped FCCS fuel loadings for the following fuel components (a) litter, (b) duff, (c) FWD, (d) CWD (see Table 1 for definitions of fuel components).

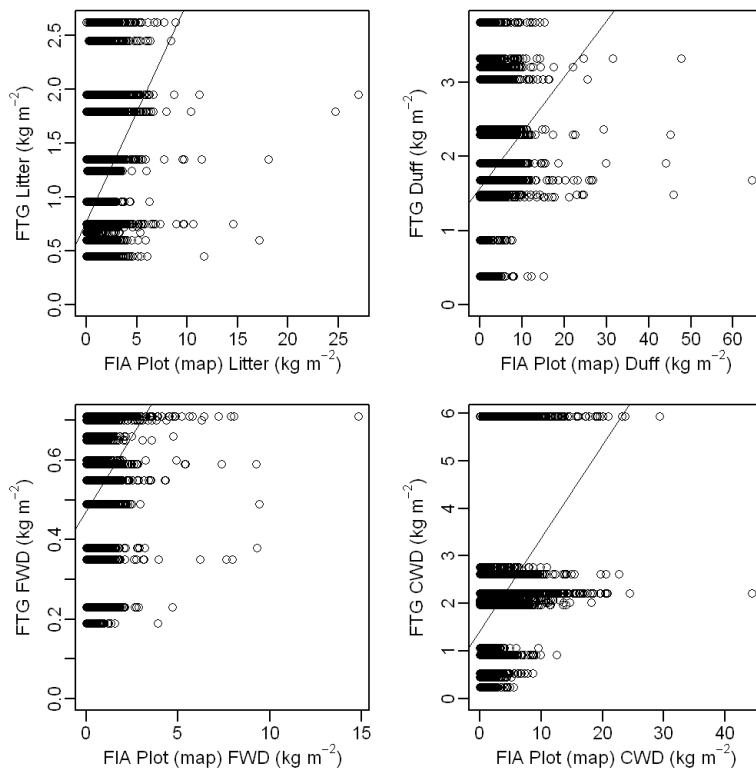


Figure 7—Relationships of measured FIA loadings to the RSAC FTG mapped FTG fuel loadings (Table 3) for the following fuel components (a) litter, (b) duff, (c) FWD, (d) CWD (see Table 1 for definitions of fuel components).

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.

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 and others 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 more difficult but 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 a brand new 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.

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.

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