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Key Points:

- Measured fuel load immediately before and after six wildfires
- Compared observed consumption to predicted for several fuel classifications
- Inaccurate fuel load predictions led to error in estimates of consumption

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Using field data to assess model predictions of surface and ground fuel consumption by wildfire in coniferous forests of California

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Abstract Inventories of greenhouse gas (GHG) emissions from wildfire provide essential information to the state of California, USA, and other governments that have enacted emission reductions. Wildfires can release a substantial amount of GHGs and other compounds to the atmosphere, so recent increases in fire activity may be increasing GHG emissions. Quantifying wildfire emissions however can be difficult due to inherent variability in fuel loads and consumption and a lack of field data of fuel consumption by wildfire. We compare a unique set of fuel data collected immediately before and after six wildfires in coniferous forests of California to fuel consumption predictions of the first-order fire effects model (FOFEM), based on two different available fuel characterizations. We found strong regional differences in the performance of different fuel characterizations, with FOFEM overestimating the fuel consumption to a greater extent in the Klamath Mountains than in the Sierra Nevada. Inaccurate fuel load inputs caused the largest differences between predicted and observed fuel consumption. Fuel classifications tended to overestimate duff load and underestimate litter load, leading to differences in predicted emissions for some pollutants. When considering total ground and surface fuels, modeled consumption was fairly accurate on average, although the range of error in estimates of plot level consumption was very large. These results highlight the importance of fuel load input to the accuracy of modeled fuel consumption and GHG emissions from wildfires in coniferous forests.

1. Introduction

The State of California Global Warming Solutions Act of 2006 (AB 32) mandated the reduction of greenhouse gas (GHG) emissions to the 1990 level by 2020. Part of the state inventory of GHG emissions is the quantification of carbon emissions and removals by forests, grasslands, wetlands, and other natural lands. A growing forest acts as a carbon sink because it removes CO_2 from the atmosphere. On the other hand, a forest experiencing high mortality due to insects and fire can act as a carbon source due to CO_2 releases [*Canadell and Raupach*, 2008; *Kurz et al.*, 2008]. In California, wildfire emitted CO_2 at an estimated rate of 18 Tg yr^{-1} in the period 2001–2008 [*Wiedinmyer and Hurteau*, 2010], contributing approximately 5% of the total estimated state fossil fuel emissions [*Wiedinmyer and Neff*, 2007]. As higher temperatures due to climate change contribute to increases in the frequency of large fires across the western U.S. [*Westerling et al.*, 2006] and the extent of high-severity fires in the Sierra Nevada [*Miller and Safford*, 2012; *Miller et al.*, 2009], carbon emissions may also increase. The densification of forests in the absence of fire, particularly in those forest types historically associated with frequent fire, can increase net carbon stocks [*Collins et al.*, 2011]. However, often these increased stocks are less stable due to greater vulnerability to wildfire [*Houghton et al.*, 2000; *Hurteau and Brooks*, 2011; *Hurteau and North*, 2009; *Rogers et al.*, 2011].

While the importance of GHG emissions from wildfires is well recognized, emissions are difficult to estimate with precision [*Wiedinmyer and Neff*, 2007]. Estimates of emissions typically rely on the use of generalized fuel characterizations to provide the necessary fuel inputs into fire effect programs. Errors in the estimates of fire emissions can come from an uncertainty in the burn perimeter [*French et al*., 2011; *Urbanski et al*., 2011], as well as estimates of fuel quantity and consumption [*French et al*., 2004; *Ottmar et al*., 2008]. A large degree of uncertainty also arises from inaccurate emission factors (the amount of a gas species emitted for a given amount of biomass consumed) [*Rosa et al*., 2011]. Addressing these uncertainties associated with fuels not only requires accurate mapping of prefire fuel loads but also quantifying the variation in fuel consumption across a wildfire [*de Groot et al*., 2007]. The challenges of mapping and characterizing fuels contribute to uncertainties in emissions estimates [*Weise and Wright*, 2013]. In addition, the use of different fuel characterizations [e.g., *Ottmar et al*., 2007] can lead to substantially different estimates of emissions [*Wiedinmyer et al*., 2006].

Sampling in the same location before and after wildfire allows for accurate point measures of fire consumption and effects [*Campbell et al*., 2007]. Fuel consumption directly correlates with emissions [*Seiler and Crutzen*, 1980] and is therefore a reliable surrogate for comparing the accuracy of emission models. Unfortunately, knowing locations and actually measuring fuels in advance of wildfire is extremely difficult. As a result, much of the information on fuel consumption in wildfires comes from “fortuitous” burning of previously established field plots. Prescribed fires offer another, more dependable opportunity to quantify fuel consumption prior to and following fire. However, because prescribed fires generally burn under more moderate fuel moisture and weather conditions, they do not exhibit the range in fire effects that is commonly observed in wildfires [*Collins et al*., 2007; *van Wagtendonk and Lutz*, 2007].

In this study, we take advantage of a rare data set that consists of vegetation and fuel measurements on the same plots taken just before and then immediately after six wildfires that occurred in California. We use this data set to assess current approaches in predicting wildfire emissions, using the first-order fire effects model (FOFEM). Our objectives were to (1) compare predicted fuel consumption for several fuel models to changes observed in the prewildfire and postwildfire fuel loads; (2) determine if the differences between modeled and observed consumption were due to inaccuracy in estimates of the prefire fuel load or the proportion of fuel consumed; (3) compare the accuracy of estimated fuel load and consumption between different fuel components, regions, and cover types; and (4) present the predicted emissions of compounds relevant to GHG inventories and air quality monitoring, both when using the field data as fuel inputs and when using the generalized fuel characterizations. The choice of FOFEM is based on its use by the California Air Resources Board, the agency responsible for GHG inventories under AB 32. Our intent was to examine readily accessible or “out of the box” fuel characterizations that input into the FOFEM and identify the one that best approximates the observed consumption. We do not evaluate potential modifications to improve the performance of FOFEM itself (e.g., emission factors and combustion efficiency). It should also be noted that this study only provides information about emissions from ground and surface fuels using FOFEM. We did not address the contribution of canopy fuels to emissions or compare the effects of different consumption models, which can also affect emission estimates [*French et al*., 2011].

2. Methods

2.1. Field Sampling

The six wildfires sampled were located in the Klamath Mountains and Sierra Nevada and burned mainly in conifer-dominated forest types (Figure 1 and Table 1). Based on the relative differenced Normalized Burn Ratio (RdNBR) [*Miller and Thode*, 2007], the six wildfires exhibited a range of fire effects. The Antelope and Clover fires were predominantly high severity, while the other fires were predominantly low severity (Table 1). All fires occurred in the summer or early fall (June to October). Field plots were located opportunistically based on anticipated fire spread. The measurements of dead and downed surface fuels, live surface fuels, ground fuels, and trees were taken in the same plots before and after burning by the Fire Behavior Assessment Team of the U.S. Department of Agriculture (USDA) Forest Service (USFS). Prefire measurements were generally taken 1–2 days prior to burning, and postfire measurements were taken within 1 week (typically 1–2 days) after burning. Trees were sampled using a variable radius approach determined by wedge prisms [*Bell and Dilworth*, 1997]. The average plot radius was 10 m, with a maximum of 49 m. Tree species, diameter at breast height (dbh, 1.37 m), and status (live/dead) were recorded for each tallied tree of dbh >2.54 cm. Litter, duff, and downed woody fuels (1, 10, 100, and 1000 h) data were collected along one or two transects in each plot using the planar intersect technique [*Brown*, 1974]. Fuel load calculations were adjusted using methods developed by *van Wagtendonk et al*. [1996, 1998]. Tree seedling, shrub, and herb fuels were

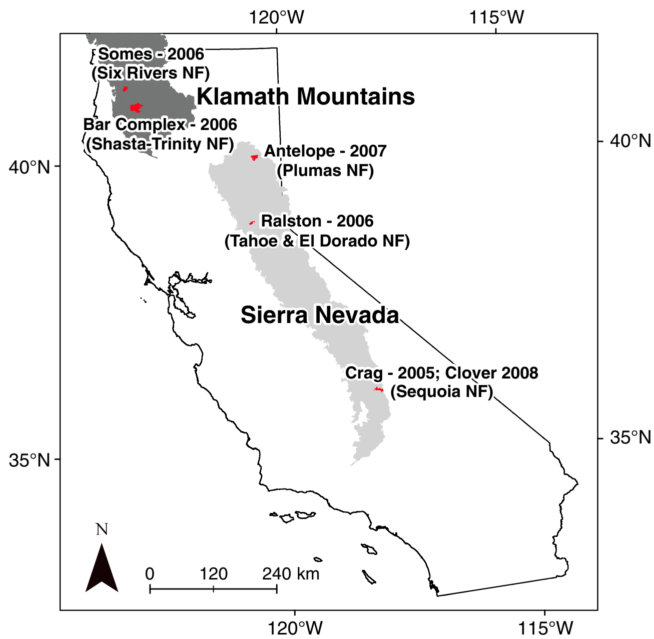

Figure 1. Map showing the location of wildfires included in the study.

sampled on transects, and fuel loads were quantified using morphological type, bulk density class, cover, depth, and proportion living following methods of *Burgan and Rothermel* [1984]. Fuel components included in the analyses were downed woody fuels, litter, duff, shrub/seedling, and herbaceous. The amount of fuel consumed by the fire was calculated as the difference between the prefire and postfire data for each fuel component.

2.2. Modeled Fuel Consumption

Fuel consumption was modeled in FOFEM version 6.0 using the consumed emissions option [*Lutes et al.*, 2013]. FOFEM predicts woody fuel and litter consumption using the Burnup model. For duff, herbaceous plants, and shrubs, FOFEM employs a decision tree to choose an appropriate consumption algorithm based on fuel model inputs [*Lutes*, 2012]. Based on the location of each plot ($n = 46$), we assigned corresponding fuel inputs from two fuel characterizations: the Fuel Characteristic Classification System Fuelbeds (FCCS) [*Ottmar et al.*, 2007] and a coupled existing vegetation—fuel model link previously established by *Clinton et al.* [2006]. The latter fuel characterization uses the Society of American Foresters/Society for Range Management (SAF/SRM) fuelbeds. These two fuel characterizations (FCCS and SAF/SRM) were of interest because they were both available for all the six wildfires and both provide the necessary fuel inputs for FOFEM. Furthermore, both of these fuel characterizations are continuous coverages that

Table 1. Summary of Fires Sampled

Fire	Year	Region	Size (ha)	Severity[a]	Area (%)	No. of Plots
Bake Oven	2006	Klamath	26,325	Unchanged	11.7	1
				Low	44.6	6
				Moderate	26.0	0
				High	17.6	0
Somes	2006	Klamath	6,275	Unchanged	27.0	4
				Low	58.3	3
				Moderate	10.8	1
				High	3.9	0
Antelope	2007	Northern Sierra	9,037	Unchanged	5.3	1
				Low	13.1	0
				Moderate	28.3	5
				High	53.3	3
Ralston	2007	Northern Sierra	3,408	Unchanged	8.9	0
				Low	52.4	9
				Moderate	29.2	5
				High	9.5	1
Crag	2005	Southern Sierra	6,389	Unchanged	20.8	0
				Low	56.3	1
				Moderate	19.0	0
				High	3.9	0
Clover	2008	Southern Sierra	480	Unchanged	21.9	0
				Low	13.0	2
				Moderate	22.6	2
				High	42.5	2

[a]Based on RdNBR values identified using the methods of *Miller and Thode* [2007].

encompass large spatial extents, offering an efficient and consistent way to quantify fuels and predict emissions across multiple fires.

In FOFEM, each SAF/SRM fuelbed has the option to select three fuel load levels: low, typical, and high. For FCCS, the typical fuel load level was the only option. This resulted in a total of four fuel characterizations per plot. Fuel moistures for FOFEM runs were based on the monthly average within each fire perimeter, developed from the archival National Fire Danger Rating System dead fuel moisture data (available from http://www.wfas.net). The decision to use coarser scale fuel moistures (monthly versus daily) is based on modeling procedures that are used for estimating criteria pollutant emissions for regional air quality modeling and emissions accounting under AB 32 (K. Scott, personal communication, California Air Resources Board).

In order to assess the performance of the four fuel characterizations (SAF/SRM low, typical, high, and FCCS) with regard to emissions, we compared the predicted emissions to those predicted using custom fuel inputs based on the prefire fuel loads for each plot. For these runs, the daily fuel moisture for 10 and 1000 h fuels was used, as determined from the Remote Automatic Weather Station data corresponding to the area and the day of burn for each plot. The day that each plot burned was determined from the daily progression maps of each fire. As duff moisture was not available, its value was inferred as the corresponding value to the 10 and 1000 h moistures used in FOFEM. The intent of this comparison was to investigate the extent to which the predicted emissions using the coarser scale inputs (fuel characterizations and monthly fuel moistures) overestimated or underestimated those based on the finer scale inputs (field fuels and daily fuel moistures).

2.3. Analysis of Field Data and Fuel Characterizations

The magnitude of difference between observed and predicted fuel consumption for each plot was assessed using regression trees. Regression tree analysis offers distinct advantages over traditional linear models because it can handle nonlinear or discontinuous relationships between variables and high-order interactions [*Breiman et al.*, 1984]. In addition, the hierarchical structure and identification of potential threshold values for independent variables are well suited for explaining ecological phenomena [*De'ath and Fabricius*, 2000]. The regression tree is constructed by repeatedly splitting the data into increasingly homogenous groups based on identified influential explanatory variables. We used the conditional inference tree technique (ctree) in the party library, within the statistical package *R* [*Hothorn et al.*, 2009]. This technique has been used to evaluate ecological relationships in forested systems increasingly in recent years, with applications such as tree crown damage from fire [*Thompson and Spies*, 2009], native tree regeneration [*Vargas G et al.*, 2013], seedling mortality and growth at treeline [*Barbeito et al.*, 2011], and probability of future forest conversion and timber harvesting [*Thompson et al.*, 2011]. Influential explanatory variables are identified using a partitioning algorithm that is based on the lowest statistically significant *P* value derived from Monte Carlo simulations. This minimizes bias and prevents overfitting of the data, which is a common problem with regression trees [*Hothorn et al.*, 2006b]. The significance level for each split was 0.05. As decision trees are sensitive to small changes in the input data [*Strobl et al.*, 2009], we assessed regression tree stability by examining the relative importance of predictor variables produced from trees constructed from 15 randomly selected start seeds using the functions cforest and varimpAUC, also available in the party package [*Hothorn et al.*, 2006a; *Janitza et al.*, 2013; *Strobl et al.*, 2007]. For each start seed, 500 trees were constructed using bootstrapping without replacement and considering all variables as a potential factor at each split. Variable importance values were normalized to the highest value for each seed and then averaged across start seeds.

Predictor variables examined were related to fuel and vegetation conditions, topography, and fire characteristics (Table 2). Topographic variables were determined from digital elevation models [*Gesch*, 2007; *Gesch et al.*, 2002] using ArcMap 10.0. The Topographic Relative Moisture Index (TRMI) was calculated using topographic position, slope, aspect, and curvature [*Parker*, 1982]. Fire severity data were obtained from the USFS Remote Sensing Applications Center and classified using the RdNBR [*Miller and Thode*, 2007]. Variables were calculated for a zone within a 40 m buffer around each plot, using the average for continuous variables and the median for categorical variables. Conditional inference trees were also used to examine the effects of plot attributes on the observed fuel consumption. In both cases, individual fuel components (e.g., litter, duff, and classes of downed woody fuels), as well as total fuel load, were assessed.

We assessed the error associated with model predictions by calculating the percent difference from the field-measured consumption, averaged by region. The average consumption observed in the field was subtracted

Table 2. Predictor Variables Used in Regression Tree Analysis to Explain the Differences Between Observed and Predicted Fuel Consumption[a]

Variable	Description
General	
Fuel input	SAF/SRM low, typical, high, and FCCS
Region	Klamath, northern Sierra Nevada, and southern Sierra Nevada
Existing vegetation	
Dominant	fir, pine, and oak[b]
Tree size class	seedling, small, and medium/large[c]
Density class	open, moderate, and dense[c]
Fuel moistures (%)	
Duff	20–40, $X = 22.6$
10 hr	6–10, $X = 6.5$
1000 hr	5–11, $X = 7.9$
Topography	
Elevation (m)	419–2657, $X = 1355$
Slope (%)	2–84, $X = 31$
Aspect (cosine transformed)	0–2, $X = 1.0$
Topographic position	lower slope, midslope, ridge, and flat
TRMI	5–51, $X = 28.2$
Fire variables	
Severity	unchanged, low, moderate, and high
Distance-to-fire-edge (m)	12–1909, $X = 523$

[a]Ranges and means (X) for continuous variables and input levels for discrete variables are also reported.
[b]Based on Calveg regional dominance classes (http://www.fs.usda.gov/detail/r5/landmanagement/resourcemanagement/?cid=fsbdev3_046815). Fir includes Douglas fir-ponderosa pine, Douglas fir-white fir, mixed conifer-fir and red fir; pine includes eastside pine, Jeffrey pine, and ponderosa pine; and oak includes canyon live oak and black oak.
[c]Classifications from the California Wildlife Habitat Relationships System [*Mayer and Laudenslayer*, 1988].

from that predicted by models, and the resulting difference was then divided by the observed fuel consumption. Since this equality is a ratio of two random variables, the standard error was approximated using the delta method [*Rice*, 2007]. The standard error and 95% confidence limits were estimated using the nonlinear mixed procedure in SAS 9.3 [*SAS Institute Inc.*, 2011].

3. Results

3.1. Fuel Loads

The differences in the prefire fuel loads between fuel characterizations (SAF/SRM and FCCS) and field data varied by fuel component (Figure 2). All fuel characterizations tended to underestimate the prefire litter loads. Prefire duff and 1000 h fuel loads were generally overestimated by fuel characterizations. This overestimation was more pronounced for the SAF/SRM high and typical scenarios. These scenarios also overestimated the 1–100 h fuel load. Prefire shrub density was more variable in the field data, but the predicted values were relatively close to the median of the field measurements (Figure 2). None of the fuel characterizations accounted for areas with very high shrub load observed in the field data (8 out of 46 plots were outliers with shrub load >35 Mg ha^{-1}). In general, median postfire fuel loads were near or equal to zero. However, the observed postfire duff loads were lower than the predicted values for all fuel characterizations.

3.2. Consumption

The amount of fuel consumed was greater on average in the Sierra than in the Klamath region (Table 3). Correspondingly, the fuelbeds representing the plots in the Klamath region tended to overestimate the fuel consumption to a greater degree than those representing the plots in the Sierra Nevada (Figure 3). There were no resulting splits in the regression trees assessing observed fuel consumption among the plots, indicating that the differences in actual fuel consumption could not be attributed to any plot characteristics we included in our models. This is likely due to the small number of plots included in the analysis. The difference in observed consumption between regions may be due to a greater amount of fuel remaining postfire in the plots in the Klamath region, rather than to the differences in initial fuel load (Figure 4).

After accounting for regional differences, fuel characterization explained most of the discrepancies between the predicted consumption and the field data (Figure 3). Within the Klamath Mountains, the relationship of similar modeled fuel consumption to observed was explained entirely by the characterization type. The FCCS and the low-fuel load option for SAF/SRM had the closest prediction to the observed total fuel consumption, although the models still overpredicted the consumption on average. In the northern and southern Sierra Nevada, among most plots, the differences were still attributable to fuel characterization type, but the

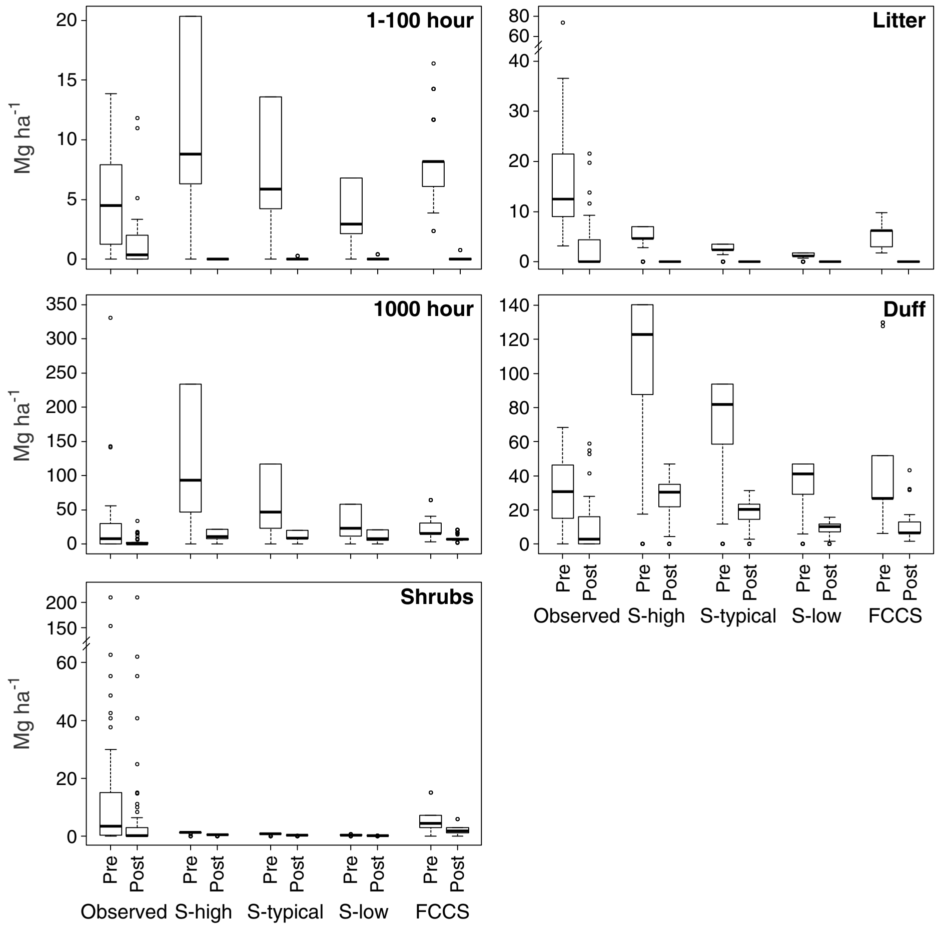

Figure 2. Prefire and postfire fuel load of the five fuel load components for the field data and the four fuel model types (SAF/SRM, low, typical and high, and FCCS). Box and whisker plots depict median (horizontal band), interquartile range (white bar), range of data within 1.5 interquartile range of the lower and upper quartiles (vertical dashed lines) and outliers (points). The data shown is for all plots with known spatial locations ($n = 46$). Note breaks and scale changes in y axis for shrubs and litter.

Table 3. Average (and Standard Deviation) of Field Plot Attributes Organized by Region and Dominant Tree Species[a]

Region/Dominant Type	No. of Plots	TRMI min–max	Consumption ($Mg\ ha^{-1}$)		Basal Area ($m^2\ ha^{-1}$)		Density (ha^{-1})	
			Klamath					
Fir	12	10–41	29	(27)	160	(170)	3000	(7600)
Oak	2	18–36	48	(9.4)	220	(240)	2100	(1200)
Pine	1	36	100		25		540	
			Northern Sierra					
Fir	8	9–39	130	(140)	98	(120)	1100	(1500)
Oak	5	5–31	71	(61)	55	(53)	460	(360)
Pine	11	17–51	62	(38)	63	(39)	1100	(620)
			Southern Sierra					
Fir	4	30–49	66	(89)	19	(5.5)	360	(320)
Juniper	1	32	82		15		600	
Pine	2	28–37	88	(110)	29	(14)	740	(710)

[a]Fir includes *Abies concolor* and *Pseudotsuga meziesii*; oak includes *Quercus kelloggii* and *Q. chrysolepis*; pine includes *Pinus lambertiana*, *P. jeffreyi*, and *P. ponderosa*; and juniper includes *Juniperus occidentalis*.

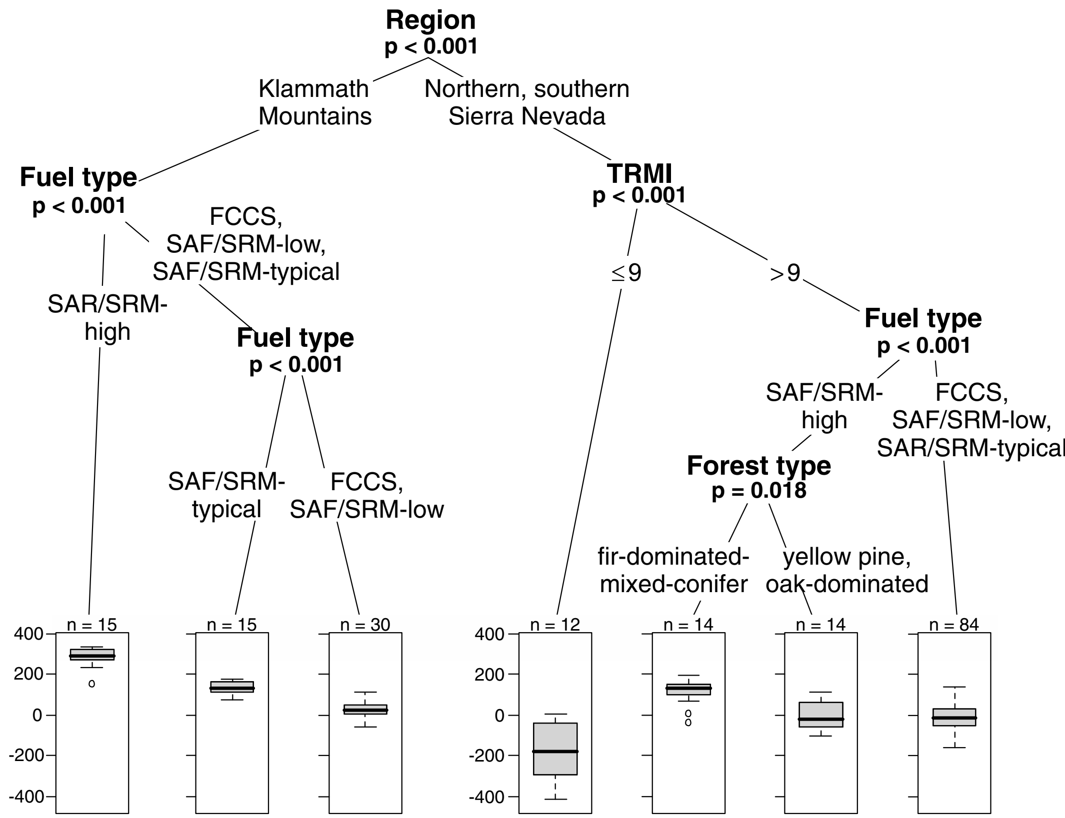

Figure 3. Conditional inference tree of the difference in the total ground and surface fuel consumption (Mg ha^{-1}) between each model and the corresponding plot data. The difference was calculated as the consumption predicted by a model minus the observed consumption for each plot. Positive values therefore indicate that the models predicted more consumption than was observed in the field data, while negative values indicate less consumption predicted than observed. Total fuel load includes litter, duff, shrubs, herbaceous, and all size classes of downed woody fuels.

relationship to modeled consumption was more complicated than in the Klamath. Drier plots (those with very low TRMI) tended to have much higher consumption than was predicted by all fuel characterizations. In addition, among the remaining plots, those with a cover type dominated by fir tended to have consumption overpredicted by the high-fuel load SAF/SRM fuelbeds. The predictions of this fuel characterization were closer to the field data for the plots dominated by pine or oak. These relationships were corroborated by the assessment of tree stability, in which region and fuel input types, followed by TRMI, were consistently ranked as the most important variables (with normalized average importance values of 1, 0.84, and 0.31, respectively). Forest type was almost the next most important variable (importance value of 0.04), but ranked just below aspect (0.05).

The average predicted fuel consumption based on the FCCS and the low and typical variations of SAF/SRM fuelbeds were closer to the observed consumption regardless of forest type, although there was a fair amount of variation within this group (Figure 3). Although predictions based on these three fuel characterizations were not differentiated by the regression tree analysis, the low SAF/SRM had a lower median prefire fuel load than the field measurements (Figure 4). In contrast, the fuel load estimates of SAF/SRM typical and FCCS were closer to the observed values; however, these two characterizations did have slightly greater postfire fuel load than was present in the field plots.

Within each region, all fuel characterizations had wide confidence intervals for the percent difference from the field data in the total fuel consumption (Table 4). As shown in the regression tree analysis, for the plots in the Klamath bioregion, there was a large difference between different fuel characterizations in the percent difference from the observed consumption, with fuelbeds within the FCCS and the low-fuel load version of SAF/SRM having closer predictions to the observed consumption. Consumption was overpredicted on average using all fuel characterizations. In the Sierras, average predicted consumption was closer to the field data. The high-fuel load variation of the SAF/SRM fuelbeds resulted in too much predicted consumption, while the other fuel characterizations generally resulted in too little predicted consumption.

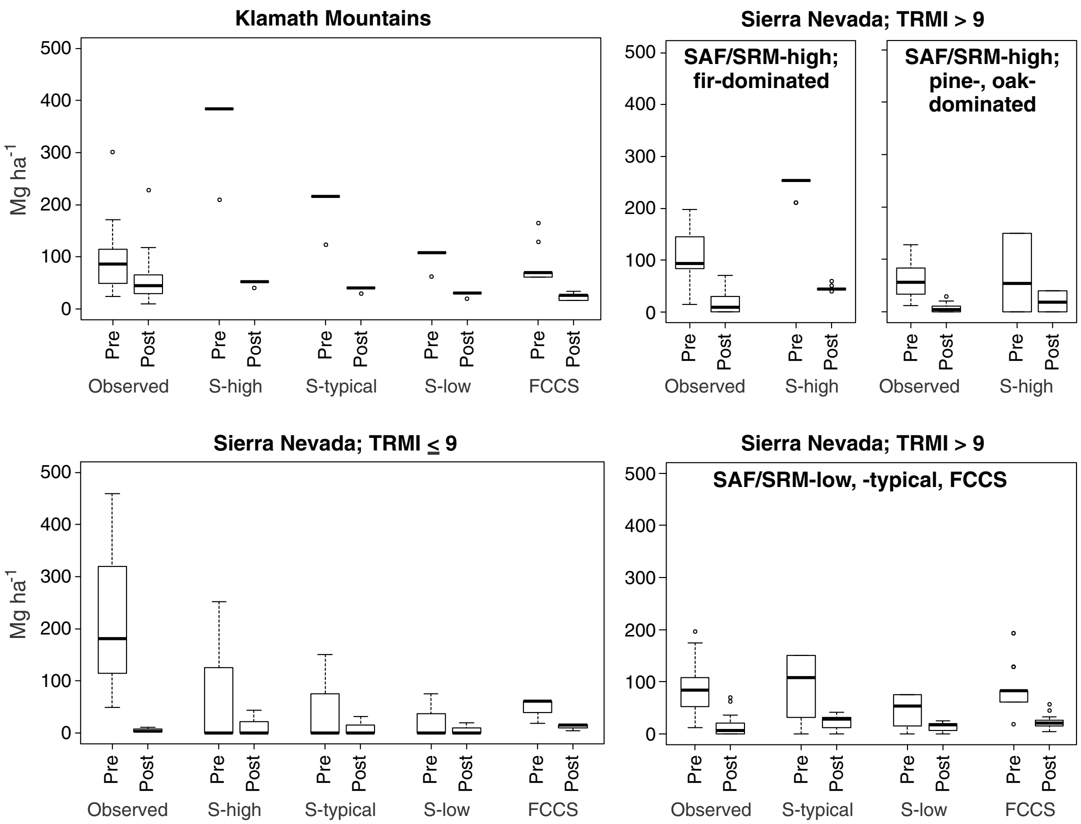

Figure 4. Comparison of field data to models, showing prefire and postfire fuel load for each terminal node in the conditional inference tree presented in Figure 3. Box and whisker plots depict median (horizontal band), interquartile range (white bar), range of data within 1.5 interquartile range of the lower and upper quartiles (vertical dashed lines), and outliers (points).

3.3. Emissions

Assessing the data for both regions, the comparisons of emissions predicted by FOFEM for the prefire field data to that predicted for the four fuel characterizations had a similar pattern to the comparisons of fuel consumption. For all emitted compounds, the amount produced from flaming was greater in the field data than in the models (Figure 5 and Table 5). The predicted CO_2 emissions for fuelbeds within FCCS were closest to the level predicted from the prefire field data (Figure 5). For CH_4 emissions, both the FCCS and low SAF/SRM fuelbeds were similar to that predicted using the field data. Among most emission species of concern to air quality, the same trends were present (i.e., SAF/SRM high and typical led to higher predicted emissions, while SAF/SRM low and FCCS were closer to the predictions generated from the field data). An exception to this trend was NO_x; the predicted NO_x emissions were greater in the field data than in all other models as this compound is only produced during flaming combustion (Table 5).

Table 4. Average Percent Difference Between Modeled and Observed Consumption of the Total Surface and Ground Fuels, With Standard Error (SE) and 95% Confidence Interval (CI)[a]

	Difference (%)	SE	Lower CI	Upper CI
		Klamath		
S high	780	630	−480	2000
S typical	370	250	−140	880
S low	110	100	−100	310
FCCS	48	85	−120	220
		Sierra		
S high	44	31	−18	110
S typical	−18	13	−45	9.0
S low	−62	5.7	−74	−51
FCCS	−28	12	−53	−3.3

[a]Positive values indicate overprediction, and negative values indicate underprediction.

4. Discussion

Our study used a unique data set to compare field measurements of surface and ground fuel consumption to that predicted by modeling. While this study provides valuable insight into fuel consumption from wildfire, a potential shortcoming is the opportunistic rather than the designed nature of the field

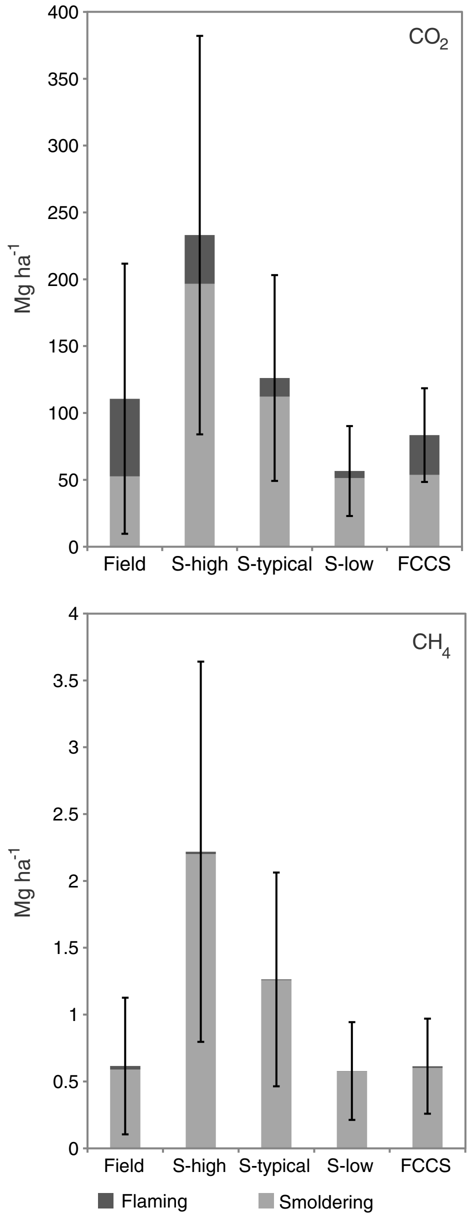

Figure 5. GHG emissions predicted by FOFEM for the prefire field data and each model type. Error bars show the standard deviation for flaming and smoldering combined.

sampling. Although we treat the plots as a random sample, they do not evenly represent the range of burn severity observed, particularly for some fires (Table 1). Field data were skewed toward representing lower fire severity areas (46% of the plots) and therefore may not adequately characterize the consumption associated with higher-severity burning (13% of the plots). Despite this limitation, the work presented still addresses a critical area where knowledge is lacking. While previous studies that measured or inferred forest floor consumption by wildfire in boreal forests have provided valuable information to the field [e.g., *Ottmar and Baker*, 2007; *Turetsky et al.*, 2011], the only similar study we are aware of looking at prewildfire and postwildfire data from a temperate forest examined only one fire in which the prefire data were collected several (5–9) years prior to burn and did not contain preburn measurements of all fuel components [*Campbell et al.*, 2007].

Discrepancies in predicted and observed fuel consumption tended to be due to the fuel models assigning a higher amount of fuel prefire than was measured in the field, with the postfire fuel load being more similar to the measured data (Figures 2 and 4). This result agrees with *Keane et al.* [2013], who found poor agreement between several fuel characterizations, including FCCS, and a large data set of fuel loads derived from forest inventory and analysis plots. In particular, the fuel characterizations we tested tended to overestimate the prefire duff and 1000 h fuel loads, especially those from the high and typical SAF/SRM. Previous work looking at uncertainty in emissions estimates also found that inaccurate predictions of fuel consumption tend to be driven by error in estimates of prefire fuel loads [*Urbanski et al.*, 2011; *Wiedinmyer et al.*, 2006]. The problems associated with inaccurate characterizations of surface fuels are not limited to wildfire emission modeling and can be attributed to their inherent spatial and temporal heterogeneity [*Hall et al.*, 2006; *Keane et al.*, 2012; *Keane et al.*, 2013] and the general inability of aerial imagery to directly detect surface fuel loads [*Jakubowksi et al.*, 2013].

In contrast to the general overestimation of prefire fuel loads, the fuel characterizations we tested estimated much lower prefire litter loads than that observed in the field plots. *Campbell et al.* [2007] similarly found that litter load was lower in the FCCS fuel inputs than in the prefire field data, attributing this discrepancy to the differences on how litter and duff were defined (however, note that subsequent revision of the FCCS fuel map improved estimates of observed fuel load in the Biscuit fire) [see *French et al.*, 2011].The fact that we found a consistent underrepresentation of litter load coupled with a general tendency to overpredict duff load across fuel models likely contributed to the differences observed in the predicted emissions of some compounds. As litter is mostly consumed in flaming combustion and duff tends to be consumed in smoldering combustion, which is less efficient, this discrepancy in prefire litter versus duff loads can lead to inaccurate attribution of emissions (e.g., greater emissions of constituents associated with smoldering (particulates) rather than flaming (oxides of nitrogen)) [*French et al.*, 2004, 2011; *Hardy et al.*, 2001; *Sandberg et al.*, 2002].

Table 5. Emissions of Concern to Air Quality[a]

	Flaming		Smoldering	
	Particulate matter ($PM_{2.5}$)			
Field	85	(110)	970	(820)
S high	54	(37)	3600	(2300)
S typical	21	(9.5)	2100	(1300)
S low	7.6	(3.6)	950	(600)
FCCS	44	(14)	990	(580)
	PM_{10}			
Field	100	(130)	1100	(970)
S high	63	(43)	4300	(2700)
S typical	24	(11)	2400	(1500)
S low	9.1	(4)	1100	(710)
FCCS	52	(16)	1200	(690)
	CO			
Field	210	(280)	13000	(11000)
S high	130	(91)	48000	(31000)
S typical	51	(23)	28000	(17000)
S low	19	(8.7)	13000	(8000)
FCCS	110	(34)	13000	(7800)
	NO_x			
Field	100	(140)	0	(0)
S high	66	(45)	0	(0)
S typical	25	(12)	0	(0)
S low	9.4	(4.3)	0	(0)
FCCS	54	(16)	0	(0)
	SO_2			
Field	33	(43)	43	(36)
S high	21	(14)	160	(100)
S typical	7.8	(3.6)	92	(58)
S low	2.8	(1.4)	42	(27)
FCCS	17	(5.1)	44	(26)

[a]Emission levels are in kg ha^{-1} and show average (and standard deviation) of the FOFEM predictions for the field data and each model type.

One aspect of fuelbeds that characterizations cannot account for at current resolutions is the significant variability that exists within a fuelbed type [*Keane*, 2013]. As was found in this study, the range of fuel loads prior to burning is typically much greater than that available in simulations [*Weise and Wright*, 2013]. Fuel maps for mountainous terrain may be less accurate due to the effects of topography on fuel load variability [*French et al.*, 2011; *Jakubowksi et al.*, 2013]. In addition, fuel particle size classes vary at different spatial scales, and this scaling may also vary by cover type [*Keane et al.*, 2012]. It is difficult to capture realistic ranges in fuel loads with current modeling approaches, which tend to represent average conditions. This is reflected in the high standard errors and wide intervals of prediction accuracy for fuel consumption in all fuel classification types (Table 4). Perhaps building in stochastic variability or some type of dynamic association with other variables (e.g., topography and canopy cover) could be incorporated in future model development.

Based on the prewildfire and postwildfire data collected, high variability existed in the observed consumption as well as in the prefire fuel loads. The total surface and ground fuel consumed ranged from 0% to 100%, with a mean of 68%. All plots showed evidence of burning, even those located within areas classified as unchanged by RdNBR, which is an acknowledged outcome for surface burns that leave the overstory unchanged [*Kolden et al.*, 2012]. Although postfire litter load was zero in the majority of the field plots, in many instances, not all litter was consumed. In contrast, FOFEM predicted 100% litter consumption for all fuel models, representing more homogenous burning. When scaling up to assess the total emissions from a wildfire, the FOFEM results can be adjusted for patchy burns by weighting the results by the percentage of area burned [*Lutes*, 2012]. However, this could be problematic when using measures such as RdNBR, where surface burn patterns may be obscured by the overstory canopy. Comparing the consumption predicted by models to that observed in prescribed fires, *Hollis et al.* [2010] also found greater variation in the observed consumption than in the modeled consumption; the models failed to represent the occurrences of extremely low or high consumption. Incorporating this variability in consumption is a challenge; however, failing to account for fire severity can lead to inaccurate estimates of wildfire emissions [*Veraverbeke and Hook*, 2013].

Postfire duff load was also zero in the majority of the plots; however, models typically predicted some duff remaining after fire. Spatial differences in duff consumption have been linked to the influence of canopy cover on duff moisture [*Hille and Stephens*, 2005], at least for prescribed burns. Other studies in California forests have found that duff moisture is related to canopy cover; however, litter and woody fuels tend to have ubiquitously low-fuel moisture that does not depend on overstory structure [*Banwell et al.*, 2013; *Bigelow and North*, 2012; *Estes et al.*, 2012].

Shrub load was another highly variable fuel component that was generally misrepresented by the fuel characterizations tested. While overall shrub density has decreased in contemporary forests with dense overstories, they do occur in fairly concentrated pockets when present [*Nagel and Taylor*, 2005]. The fuel models we tested generally predicted a very low shrub load, which is representative of the majority (72%) of the plots we sampled. However, 17% of our plots had a very high shrub density, corresponding with live fuel loads ranging from 38 to 210 Mg ha^{-1}. This demonstrates that patches of high shrub density that may occur within predominantly forested cover types can contribute a significant proportion to the total fuel consumption and thus emissions, which may be overlooked by fuel classifications.

5. Conclusions

In order to account for wildfire emissions across large spatial scales, agencies rely on wildfire emission models coupled with remote sensing-based fuel characterizations. Based on our results, it appears that the FOFEM coupled with either fuel classification type we analyzed (FCCS or SAF/SRM) can perform reasonably well for predicting surface and ground fuel consumption by wildfire. For the total surface and ground fuel consumption, the FCCS and the low-fuel loading option for SAF/SRM performed very well in both regions on average. It should be noted that in the Sierra Nevada, the typical fuel load option for SAF/SRM also provided predictions close to actual consumption. Perhaps combining the fuel components compensated for fuelbed errors among different fuel load components (i.e., low predictions of litter load may have been compensated for by high predictions of duff load). While these models were fairly accurate on average, the confidence intervals associated with the percent accuracy in our data set were very large. Therefore, predictions at the level of an individual plot may err considerably, but when assessing a larger area, the predicted consumption may be closer to what was observed in our data.

Among the pine and oak-dominated sites in the Sierra Nevada, the high-fuel load SAF/SRM option also gave fairly accurate estimates of consumption. A limitation to our analysis is the lack of fuel data associated with oak-dominated cover types for the SAF/SRM classifications in FOFEM. These fuelbeds are provided in FOFEM only as a customizable option with user-defined inputs, with "default" values of zero. We chose to run the model as it was (i.e., no fuel load prior to burn). Although only six plots in our data set were categorized with an oak-dominated cover type under SAF/SRM, this still may have affected our results. Because of this limitation, when site-specific information is lacking, the FCCS cover types may be preferable for generating estimates of emissions for oak-dominated areas.

The estimates of GHG emissions (CO_2 and CH_4) using the FCCS or the low-fuel load scenario for the SAF/SRM fuelbeds were also close to that predicted using the field data as the FOFEM inputs. Some differences existed for predictions of emissions of compounds more exclusively associated with either flaming or smoldering, particularly among the SAF/SRM classifications. The FCCS fuelbeds had a higher estimated litter load than those in the SAF/SRM characterizations and were therefore closer to the field data, so the emissions predicted using these fuelbeds were closer in general to those estimated using the field data.

Although California is one of the few states that require GHG inventories, interest in emissions accounting elsewhere is broad. Wildfires can contribute a substantial quantity of GHG emissions although the contribution is generally pulsed and unpredictable. While it is clear that some error is associated with predictions generated from the modeling framework evaluated in this study, it is important to understand how much error there may be and what potential adjustments can be made to minimize it. This study only examined modeled consumption and emissions in conifer forests. Future work should be done to get a better representation of fuel consumption in different vegetation types (e.g., chaparral). A better understanding of the discrepancies between modeling efforts and wildfire effects can improve the ability of agencies to inventory GHG emissions.

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