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Towards an Uncertainty Analysis of WFEIS and the USFS CONSUME Model

Amanda G. Grimm, Amy L. Howes, Nancy French, Brian Thelen, Naomi Hamermesh

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Abstract

WFEIS is an online fuel emissions estimation tool for wildland fires based on the USFS FERA's CONSUME software application. For WFEIS to be most useful, the potential sources of error in its estimates need to be quantified. Here, we present first steps towards a comprehensive framework for estimating the various components of WFEIS model uncertainty using specific model components—shrubs and small (0-100-hr) western woody fuels—as a case study. We discuss the analysis, options for model improvements based on our results, and additional potential sources of error outside the scope of this case study. Finally, we outline what would be involved in a comprehensive uncertainty analysis of the entire WFEIS model.

Background

Once regarded as being of little importance to carbon cycle science, wildfires are now recognized as a significant factor in global carbon dynamics and one of the main pathways for the movement of carbon from terrestrial pools to the atmosphere. Given the increased interest in wildfire in the context of carbon studies, improved models and estimates of fire emissions are needed. The Wildland Fire Emissions Information System (WFEIS) is a geospatial data system that integrates fire perimeter maps with spatially explicit fuel consumption and fuel loading data layers to model fuel emissions from wildland fires. WFEIS relies on the Fuel Characteristic Classification System (FCCS) (Ottmar et al. 2007, Riccardi et al. 2007a, 2007b) developed by the USFS Fire and Environmental Research Applications (FERA) Team for fuel loading inputs and on CONSUME, a software application also designed by USFS FERA, to generate fuel consumption and emissions estimates for multiple combustion phases.

CONSUME predicts fuel consumption and emissions by combustion phase, stratum and fuelbed. For some strata, it includes separate equations to calculate the consumption of activity and natural fuel types. These equations are mostly derived from regressions fitted to field data, so naturally there is some error associated with the measured field values as well as the regression coefficients. Additional error is introduced when CONSUME results are made spatially explicit via WFEIS.

To better understand the reliability and accuracy of the estimates produced by WFEIS, it is necessary to conduct uncertainty and sensitivity analyses to evaluate the various potential sources of error in the estimates produced by CONSUME. For WFEIS, these potential sources include error in input measurements (e.g., the weather data used to estimate fuel moisture); errors in the fuelbed and burn area maps utilized as model inputs (including misclassifications, spatial resolution issues and mixed pixels); and coefficient errors in CONSUME's regression-based prediction equations. In collaboration with the FERA team, MTRI is currently working to develop a framework for estimating the various components of WFEIS model uncertainty. Identification of the sources and quantification of the magnitude of uncertainty will help to better understand the contribution of each source to the overall accuracy and prevision of the WFEIS estimates and to prioritize efforts for its further development. Here, we present our recent progress towards such a comprehensive framework, including a mathematically rigorous documentation of CONSUME and case studies of two specific components of the model—shrubs and natural small (0-100-hr) western woody fuels—using a sample-based approach to uncertainty analysis.

Descriptions of Focal Components of CONSUME

Shrub Consumption

CONSUME uses the same shrub consumption equations for both natural and activity fuel types. The CONSUME shrub consumption model uses a generalized linear model (GLM) to confine modeled results for the proportion of loading consumed to between 0 and 1. Total shrub consumption $S(f)$ (tons/acre) is calculated using the following inputs:

Shrub loading $W_S(f) = W_{S1}(f) + W_{S2}(f)$,

where $W_{S1}(f)$ and $W_{S2}(f)$ are the primary and secondary shrub loadings (Mg/ha), respectively, provided by FCCS for a given fuelbed, the secondary shrub layer being optional;

Percent black $\%b$ = the percentage of the shrub stratum blackened by the burn; $\%b$ is input by the WFEIS user with a default value of 50%.

Shrub consumption is then estimated as follows:

$$S(f) = W_S(f) \cdot P_S$$

where

P_S = proportion of loading consumed = $\frac{e^Y}{1+e^Y}$

and

$$Y = -2.6573 + \left(0.0956 \cdot W_S(f)\right) + (0.0473 \cdot \%b)$$

The coefficients of Y were established based on a study of prescribed fires in big sagebrush (*Artemisia tridentata*) rangelands throughout the intermountain West (Wright and Prichard 2006a). Plots were destructively sampled pre-fire and post-fire to measure shrub loadings, fuel moisture content, live fuel moisture, the live/dead ratio, and fuel consumption in the field. The equations developed from these data were then used to estimate shrub consumption in all regions. The 17 samples reported in Wright and Prichard (2006a) were supplemented with an additional 9 samples collected in western Montana in a recent revisit of fuel consumption estimation for sagebrush (Wright 2013); these samples are also utilized in the uncertainty analysis reported here.

Western Woody Fuel Consumption

The "woody fuel" stratum comprises sound and rotten downed woody fuels, not including stumps or woody fuel accumulations (piles). As a second case study, we evaluated the uncertainty for a subset of the Western equations for estimating the consumption of woody fuels, specifically the 1-hour (<0.25 in diameter), 10-hour (0.25 to 1 in) and 100-hr (1 to 3 in) fuels (SW_1, SW_{10} and SW_{100}, respectively).

In the case of woody fuels, CONSUME uses separate equations for activity and natural fuel types. For natural fuels, equations were developed based on a surface fire consumption study of 60 prescribed burn units located in

Ponderosa Pine-dominated forests in Arizona, eastern Oregon and eastern Washington with no recent logging activity (Wright and Prichard 2006b). 1-hr fuels are simply estimated as follows:

$SW_1 = W_{SW1}(f),$

where

$W_{SW1}(f)$ = the estimated preburn loading of 1-hr fuels derived from FCCS.

10-hr and 100-hr fuels are similarly estimated as

$SW_{10} = W_{SW10}(f) \cdot 0.8650$ and
$SW_{100} = W_{SW100}(f) \cdot 0.7844,$

respectively.

The CONSUME models of woody fuel consumption for activity fuels (fuels resulting from or altered by forestry practices such as timber harvesting or thinning) assume that all 1-hr and 10-hr are consumed during the flaming phase of a burn, and consumption of 100-hr fuels is estimated based on a combination of assumptions about management objectives associated with such burns and fuel consumption theory. Activity fuel consumption equations are not analyzed here.

CONSUME Documentation

Given CONSUME's complexity, in order to conduct any sort of uncertainty analysis for WFEIS, it's important to have the complex mathematical formulas used in the CONSUME module written out in a mathematically rigorous way. These formulas were extracted from the CONSUME code and are included as an appendix at the end of this report.

Data Exploration and Sample-Based Model Evaluation

Shrub Consumption

Plotting the sample data tells us whether there is a correlation between any of the variables in the model (Figure 1). Obvious to the eye, percent black (the percentage of the area burned, post.percent.black) and the proportion of the shrub loading consumed (prop.sage.cons) have a linear relationship. There is no obvious pattern between prop.sage.cons and pre-burn sage loading (pre.total.sage.load) or between post.percent.black and pre.total.sage.load.

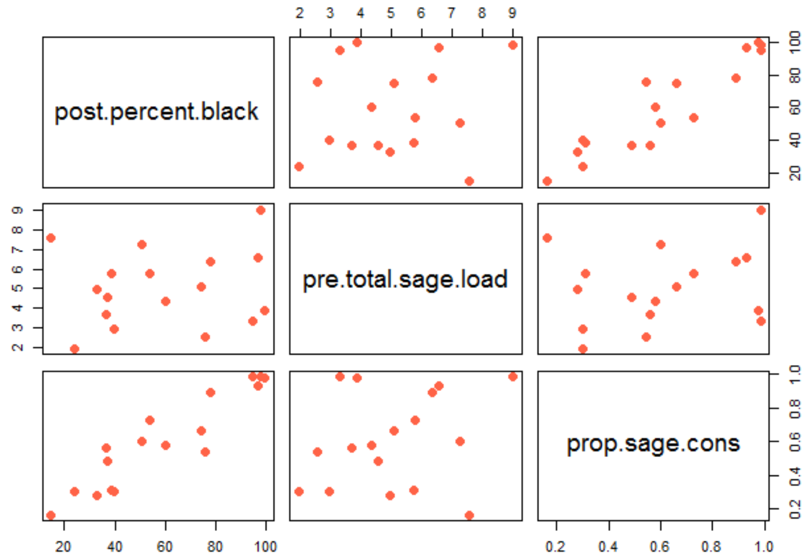


Figure 1: Scatter plots of shrub consumption input variables and proportion consumed.

Once we fit our model, plotting the actual vs. modeled values for total shrub consumption helps in visualizing the model's goodness of fit (Figure 2). All points hover closely to the true data, so the fit is good.

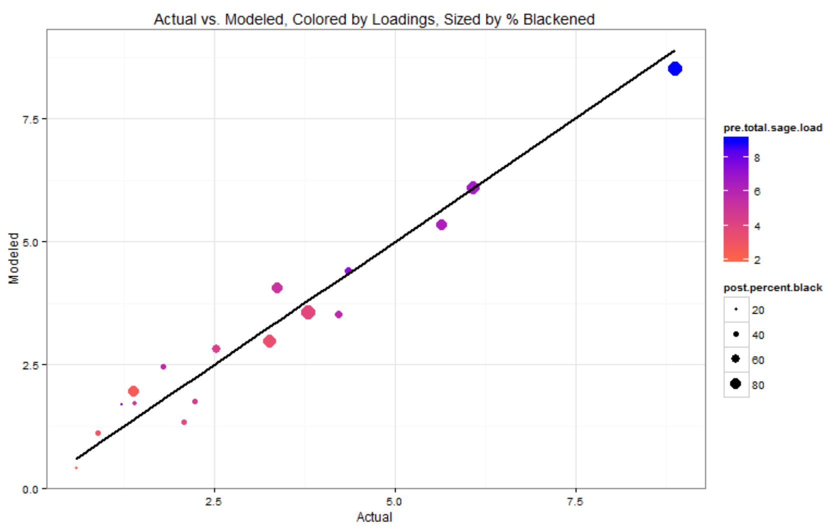


Figure 2: Sampled vs. modeled values for shrub consumption, where marker size corresponds to percent black and marker color to pre-burn shrub loading (cooler color = higher load).

In WFEIS, since most users do not have access to a robust estimate of percent blackened, a user can manually enter their own estimate or use the default value of 50%. Because users presumably resort to the default often, this analysis will focus primarily on the error associated with a predicted 50% value. Figure 3, like Figure 2, plots actual vs. modeled shrub consumption (same as above) but with another set of predicted proportions overlaid on top. The yellow values represent the shrub consumption predicted using a value of 50 for percent blackened. It is clear that the fit is not as tight, and the error, as expected, does significantly increase.

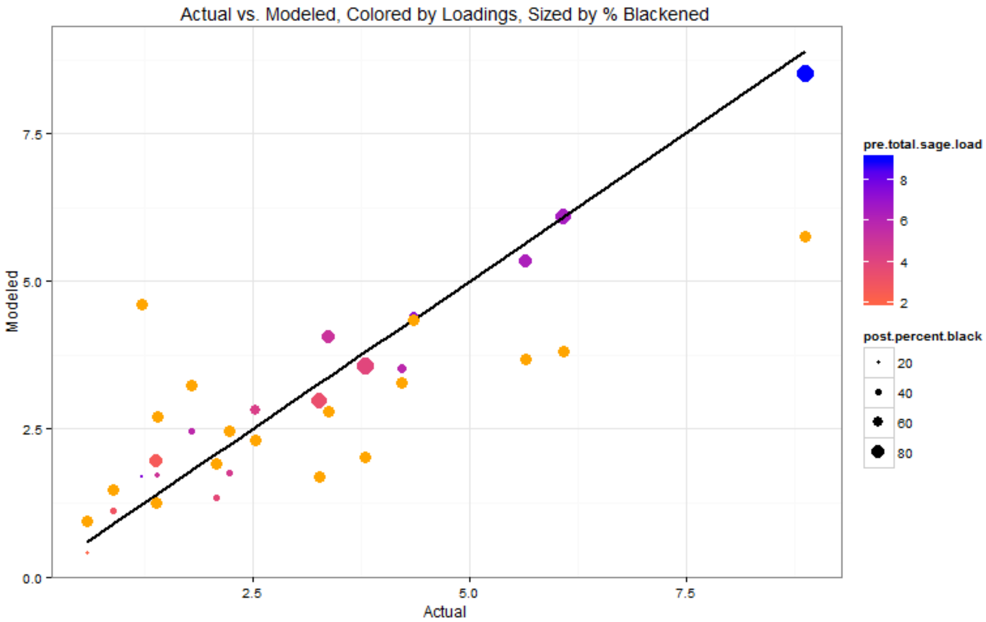


Figure 3: Sampled vs. modeled values for shrub consumption. The model output using sampled values of percent black and using a 50% default value are plotted for each of the 17 original sample sites. Marker size corresponds to percent black and marker color to pre-burn shrub loading (cooler color = higher load).

Table 1 reflects the patterns that can be observed visually in Figures 2 and 3. Pre-burn shrub loading is approximately normally distributed with a smaller standard deviation, whereas the distribution of percent black is approximately uniform, with a much higher standard deviation (Figure 4). Both pre-burn shrub loading and percent black are positively related to shrub consumption, though the strong correlation between percent black and proportion consumed and the lack of a relationship between loading and proportion consumed are evidenced by the respective p-values of those coefficients in the model. The large standard error of shrub loading and small SE of percent black also reflect their relative significance.

Table 1: Parameters of shrub consumption and its input variables in the CONSUME equation along with their coefficients and standard errors in the regression.

	Standard Deviation for Input Variable Sample Values			
Variable	**Mean**	**Range**	**SD**	
Pre-burn shrub loading (tons/acre)	5.1042	1.963, 9.0113	1.9199	
Percent black	59.2	14.5, 99.8	28.08105	
Shrub consumption (tons/acre)	3.2023	0, 23.7825	2.874138	
	Standard Error for Regression/Prediction Coefficients			
Coefficient Variable	**Coefficient**	**SE**	**Z**	**Pr(>|z|)**
Intercept	-2.65726	2.19058	-1.213	0.2251
Pre-burn shrub loading	0.09560	0.34663	0.276	0.7827
Percent black	0.04728	0.02558	1.848	0.0646

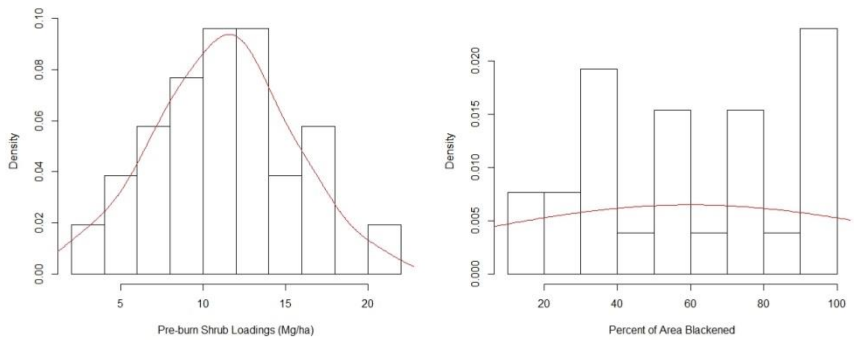


Figure 4: Histograms of sample data for input variables overlaid with kernel density lines. Pre-burn shrub loadings (left) and percent blackened (right) from Wright 2013.

A prediction confidence interval provides an estimated range of values with so much confidence of including an unknown population parameter, typically 95%. A confidence interval is calculated from the predicted value and its standard error. Figure 5 visualizes the confidence intervals for each site in the western sagebrush dataset. In the figure, the black points represent the measured proportion of the shrub loading consumed (P_S), while the purple is the predicted P_S using the measured post.percent.black values. Confidence intervals represent SE*1.96 and were computed on the scale of the linear predictor (in R, by using predict.glm() with type="link") and then mapped from the linear predictor scale to the response scale by applying the inverse of the link function (exp(x)/(1 + exp(x))). Most of the black and purple markers are fairly short distances from each other, and all measured values fall within the CIs of the predicted values. Then, plotted on top, the yellow markers represent P_S predicted with the default percent blackened input value of 50%. All of the predicted P_S values using 50% as the input for percent blackened are also within the confidence interval of the purple markers, though some are close to the limits, especially for the largest and smallest 'true' values of percent black (left and right ends of the plot), which is expected, as these values are furthest from 50%.

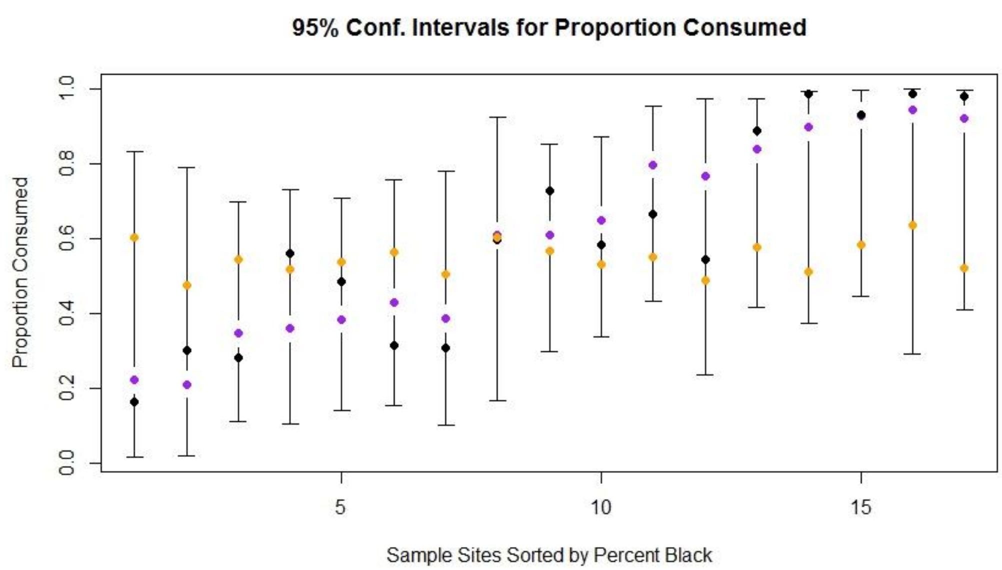


Figure 5: Fitted estimates of proportion of shrub loading consumed using measured values of % blackened (purple), actual values of proportion consumed (black) and values predicted using % blackened = 50 (yellow). Sample sites are ordered by increasing percent black. Error bars indicate the 95% confidence interval of the predictions made using measured percent black.

It is important to observe how each variable reacts while the other is held constant. This will indicate which variables influence the predictions and also how each variable is related to the dependent variable. First, P_S was predicted holding pre.total.sage.load constant at different values and using the measured values of percent black (Figure 6).

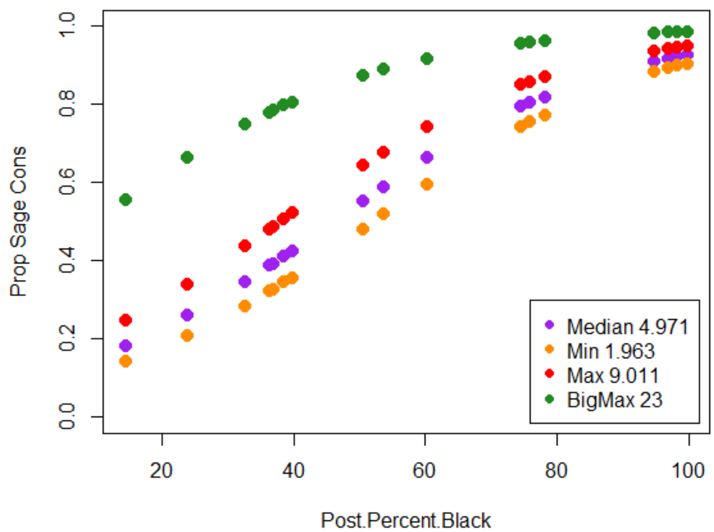


Figure 6: Predicted proportion of shrub loading consumed holding pre-burn sage loading constant at different values and using measured values of percent black.

Our original 17 shrub consumption observations have pre-burn shrub loading values ranging from 1.963 to 9.0113 tons/acre with a median value of 4.971 tons/acre. The "BigMax" value of 23 represents the maximum value of an additional 309 loading values from burns where percent black was not measured (from FCCS fuelbed loading data). It also represents an extremely high loading value that allows us to visualize an extreme effect. This exercise confirms that there is definitely a positive correlation between post.percent.black (percent blackened) and the predicted proportion consumed. Next, P_S was predicted holding percent black constant at certain values to visualize what happens when pre-burn shrub loading is plotted against predicted P_S (Figure 7).

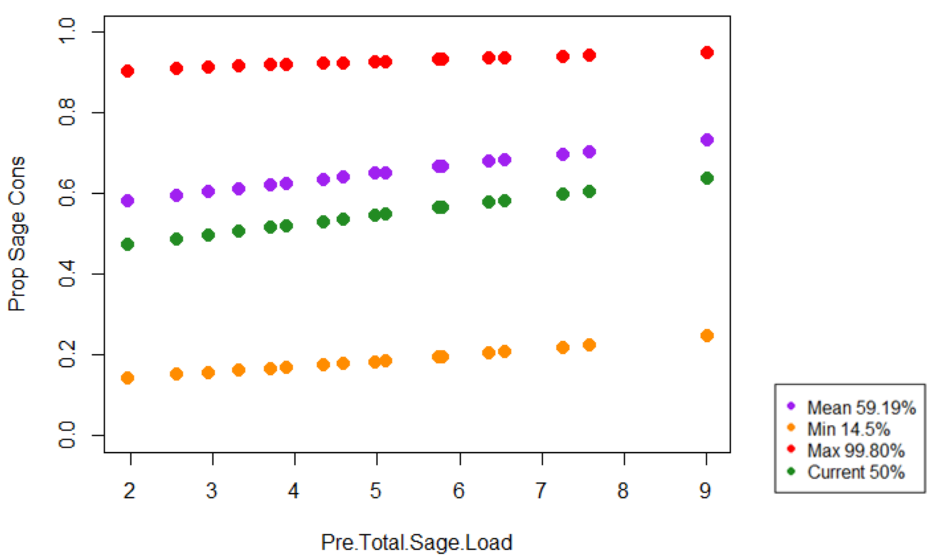


Figure 7: Predicted proportion of shrub loading consumed holding percent black constant at different values and using measured values of pre-burn shrub loading.

The results here are much different. Here, as pre.total.sage.load increases, the predicted proportion consumed almost stays constant (it has a very slight increase). This is a visual confirmation that, in line with their associated p-values, pre.total.sage.load is not very influential to our prediction, whereas post.percent.black variable is. It is also observed from Figure 7 that the predicted proportion consumed hovers closely (roughly within ± 0.2) to the post.percent.black input value. For example, using our current default of a 50% blackened input value (green points on plot), the predicted proportion consumed hovers between 0.4 and 0.6.

WFEIS estimates include many sources of error, including measurement error in the field data used to determine equation coefficients, error in the loadings derived from FCCS fuelbeds, error in the user inputs, and spatial error introduced when CONSUME estimates are made spatially explicit in WFEIS (e.g., error in burned area boundaries, limitations associated with Landsat or MODIS pixel size). Using the sample data, we can roughly characterize the sensitivity of the shrub consumption model to its two input variables by visualizing the effects of introducing different amounts of error in each input. First, we examine the effect of different magnitudes of error in the shrub loading value (Figure 8).

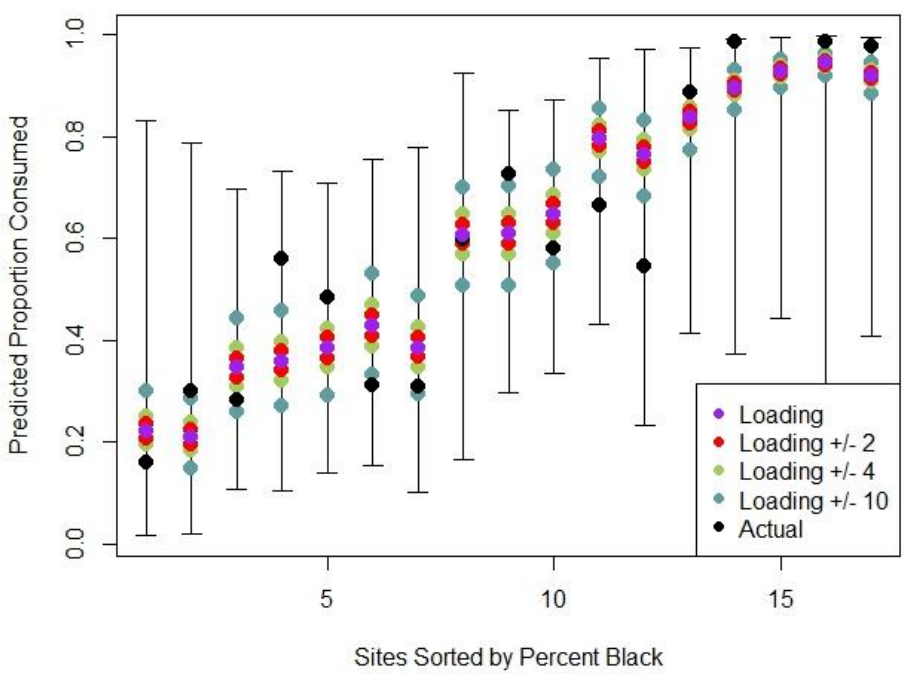


Figure 8: Sensitivity of proportion consumed to error in pre-burn shrub loading. Red, green and blue points indicate the predicted proportion consumed when the loading value used is 2, 4 and 10 Mg/ha more or less than the measured value, respectively. Error bars represent the 95% confidence interval for the predictions made using the measured values of pre-burn loading.

The model sensitivity is represented by the red, green and blue dots. For example, the green points are the predicted proportions consumed if the loading value used is approximately 4 Mg/ha different than the true loading values. The very first site has a loading value of 4.97 Mg/ha. The upper red point, then, represents the predicted proportion with an 8.97 Mg/ha loading value and the true percent blackened value of 32.7%. In some cases, the actual proportion can be almost accurately predicted even with a large error in the loading value. In other cases, the introduction of error actually increases the accuracy of the prediction. Regardless, Figure 8 shows that error caused by inputting an incorrect loading value (within a reasonable amount) will not be significantly larger than the error produced with the true loading values. The blue dots represent more dramatic errors in pre-burn loading of 10 Mg/ha. Roughly half of the predictions based on dramatic error are a bit off, but the other half are fairly close to the other prediction values. In practice, error in pre-burn shrub loading could be introduced by the error in FCCS fuelbed loading estimates or by spatial error if the burned area is misclassified.

FCCS Fuelbed Shrub Loading Values

How do our 17 observations in the western sagebrush shrubland data compare to the 309 FCCS fuelbeds with shrub loading values? The probability density plot below (Figure 9a) represents our 17 observations used to create the model. Overlaid on the plot is a blue density line representing all 309 values. Figure 9b is the same illustration but vice versa. Our 17 observations range from 1.963 to 9.0113 with a median of 4.971, while all the shrub loadings range from 0 to 23.7825 with a median of 1.296. A majority of all shrub loadings fall between 0 and 2.721 tons/acre, with only 12 values being greater than 9.22 tons/acre. The western sagebrush data is a fair representation of all shrub loadings because it includes at least one value that falls within almost all of the loading value classes from the larger FCCS set.

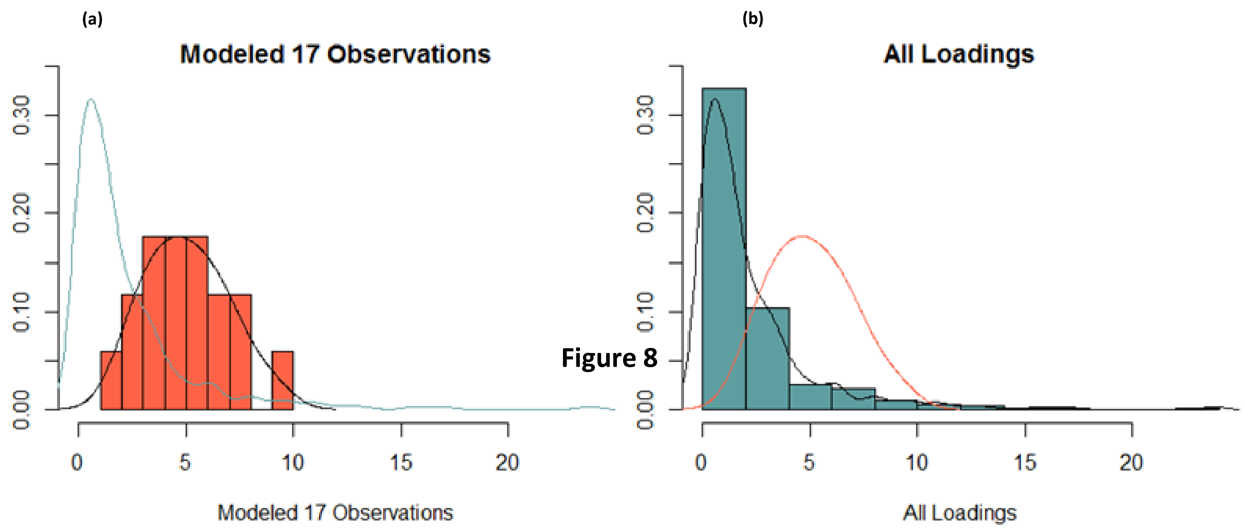
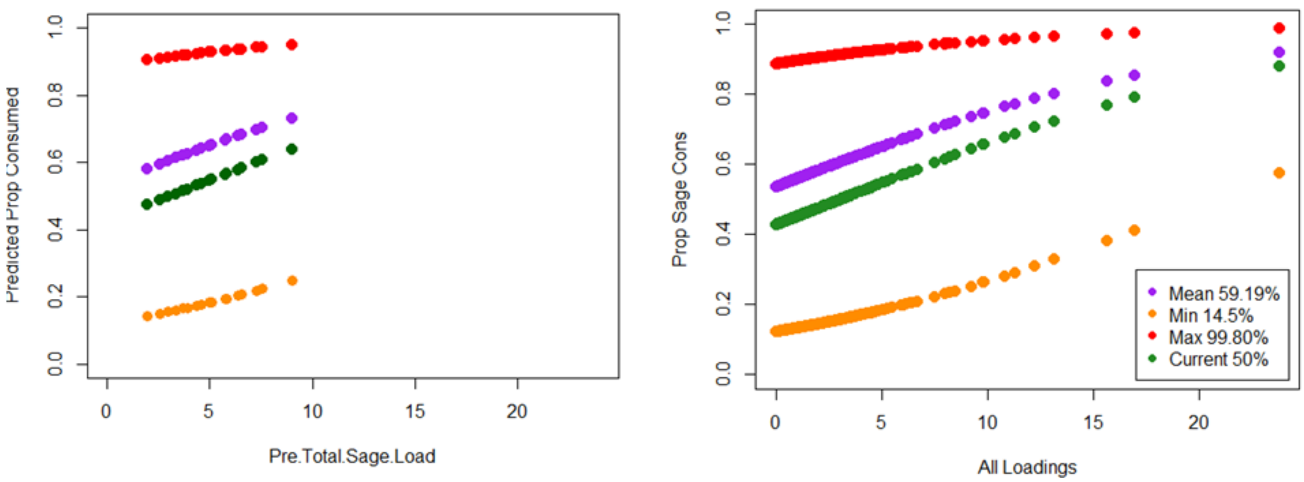


Figure 9: Comparison of shrub loadings for a) the 17 observations used to parameterize the CONSUME shrub consumption equation and for b) 309 additional observations of shrub consumption.

In turn, we can also visualize the effects of holding post.percent.black constant when applied to the data used to construct the construct the CONSUME shrub model (Figure 10a) vs. all shrub loading values (

Figure 10b).



(a) **(b)**

Figure 10: Effect on proportion of shrub layer consumed of holding percent black constant at different values, for a) the 17 observations used to build the model and b) 309 shrub loadings from FCCS fuelbeds.

The x-axis denotes the true shrub loading values, and the y-axis corresponds to the predicted proportion consumed using the post.percent.black input value specified in the legend. There is again a slight linear increase in the predicted proportion consumed with pre-burn loading, but the proportion consumed still hovers closely around the post.percent.black input value (now roughly within ± 0.4 because of the expanded range of the dataset). For example, using our current default of a 50% blackened input value (represented by the green points on the plot), the predicted proportion consumed values hover between 0.4 and 0.8.

To view this information a little differently, we can plot the confidence intervals around each predicted proportion consumed (Figure 11). Here, the x-axis represents each individual site (site 1–309), which are sorted from the smallest loading value to the largest. The y-axis here is again the predicted proportion consumed using a post.percent.black input value of 50%. Most predicted values for proportion consumed (minus the tail end for extremely high loading values) lie between 0.4 and 0.6. Most of the standard errors are too large to even see the confidence intervals. The predicted values with confidence intervals that are present have loading values between roughly 1 and 3 tons/acre.

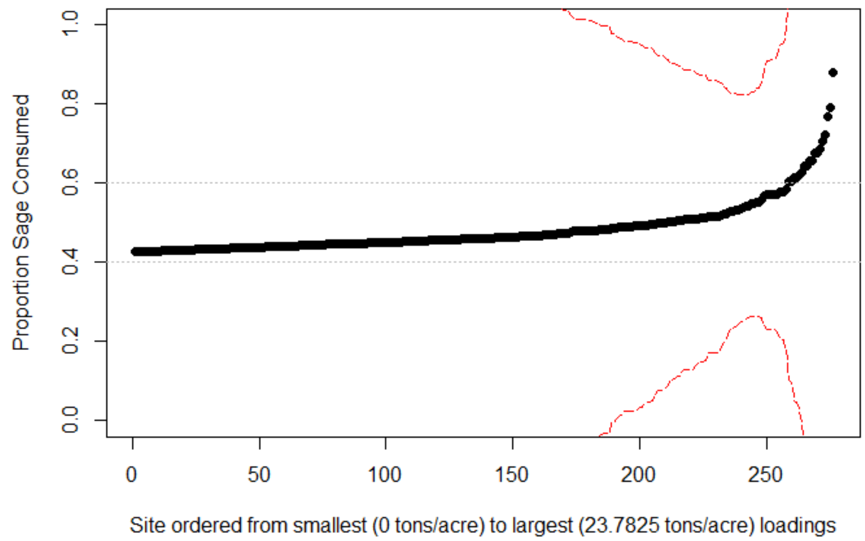


Figure 11: FCCS dataset of pre-burn fuel loadings vs. predicted proportion consumed with 95% confidence intervals (dashed red lines).

Error

Shown in Table 2 are the summary statistics for both our predicted proportion consumed using our true 17 observations and our predicted proportion consumed using our 17 observations but with a input value of 50% for post.percent.black.

Table 2: Summary statistics for predicted proportion consumed using true and default values of percent blackened.

	With True % Blackened	With 50% Blackened
Sum of Residuals	0.00000005524	0.9851413
Min. Standard Error	0.09477784	0.1439863
Mean Standard Error	0.167959	0.2036988
Max. Standard Error	0.2536776	0.3562659

Figures 12 and 13 illustrate the statistics from Table 2.

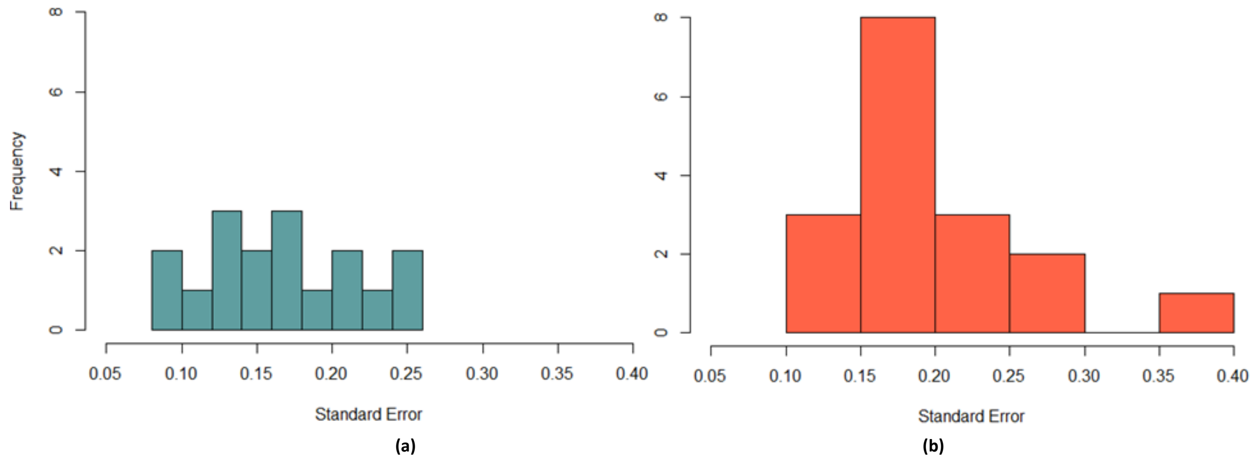


Figure 12: Histograms of standard error for proportion consumed predicted using a) the measured values for percent black and b) the default value of 50%.

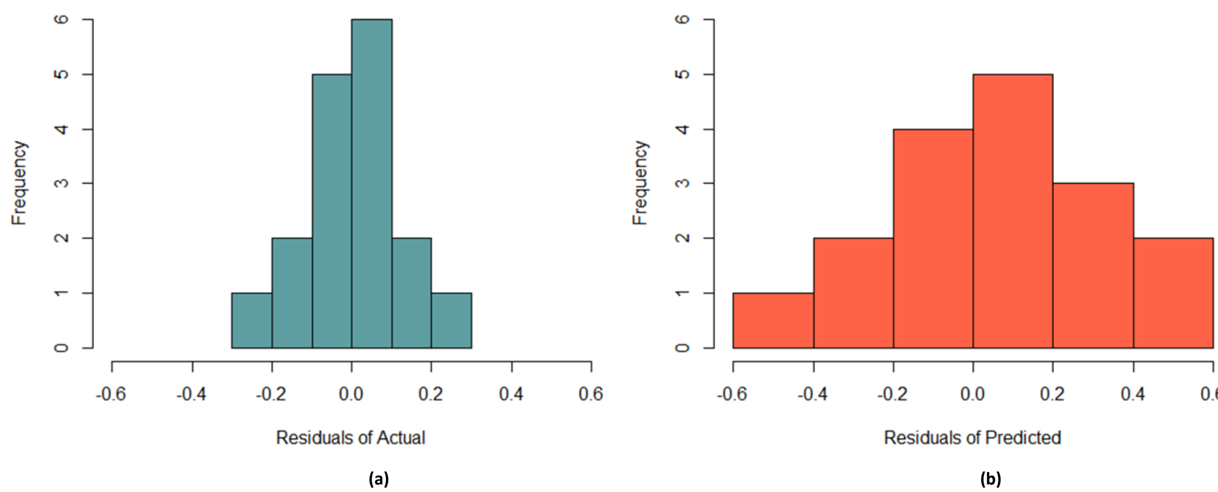


Figure 13: Histograms of error for proportion consumed predicted using a) the measured values for percent black and b) the default value of 50%.

Both illustrations compare the error for the two scenarios. We could have guessed that inputting estimated values for an influential variable would have significantly higher errors than inputting true values. What we want to know is, quantitatively, how much error is introduced relative to using the true values. If we focus just on our model and the 17 true observations, our model does fairly well. The residuals are closely knit around zero (Figure 13a), and our largest standard error is 0.25 while a majority of our standard errors are close to 0.16. What is important is what happens when we take this model and apply it to a shrubland where we do not know these true values.

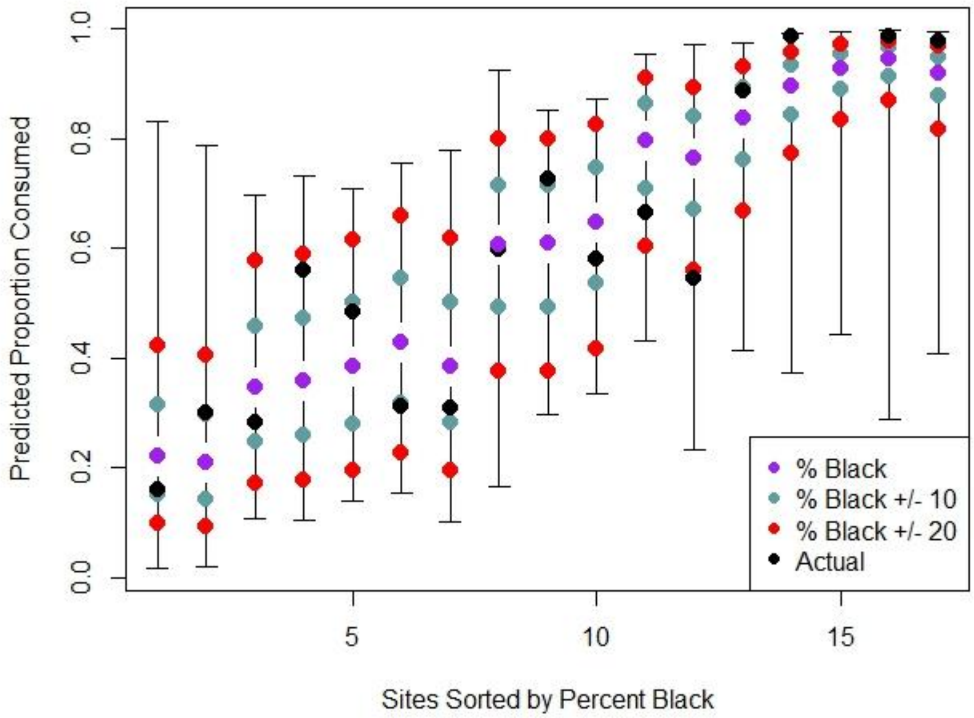


Figure 14: Sensitivity of the modeled proportion of shrub loading consumed to the input value for percent black. Plotted are the model outputs using the sample values of percent black (purple) and those values ± 10 (blue) and 20 (red) as well as the actual proportion consumed (black). Error bars represent 95% confidence intervals of the proportion consumed predicted using measured percent black.

The model sensitivity when inputting a percent blackened value that is not a measured value is shown in Figure 14. The x-axis represents each individual site ordered by increasing percent black, and the y-axis is the predicted proportion consumed based on certain variable inputs. The purple circles represent the predicted proportion consumed using the measured values for percent black, the red circles represent predictions using the measured percent black value ±20%, and the blue circles ±10%. Finally, the black circles represent the measured values for proportion consumed. For example, for the first site, the true percent blackened value is 32.7%. Therefore, the red circles represent input percent blackened values of 12% and 52% and the blue circles 22% and 42%.

All predicted values that use a percent blackened input value within ±20% of the measured value fall within our confidence intervals. Unfortunately that is not all that informative because the confidence intervals are fairly wide.

Western Woody Fuels Consumption

Recall that 1-, 10- and 100-hour Western woody fuel consumption is estimated as follows:

$SW_1 = W_{SW1}(f),$

$SW_{10} = W_{SW10}(f) \cdot 0.8650,$

$SW_{100} = W_{SW100}(f) \cdot 0.7844$

To begin, we can visually assess the fit of the model by plotting fuel consumption vs. pre-burn loading for the 10- and 100-hour fuel class data from Wright and Pritchard (2006b) and overlaying the linear relationships used by

CONSUME (Figure 15Figure 2) (the Wright and Pritchard dataset does not include the 1-hr fuel class). The measured data points correspond fairly closely to the linear relationships used by CONSUME (adjusted R^2 = 0.976 for 10-hour fuels, 0.917 for 100-hour fuels), so the fits are good. The standard errors for the CONSUME models are 0.017 and 0.029 for 10- and 100-hour fuels, respectively.

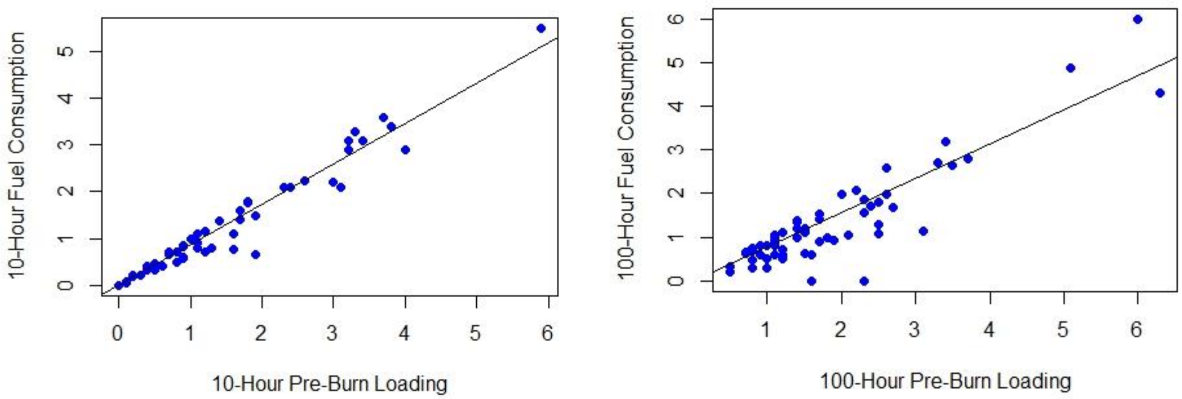


Figure 15: Pre-burn fuel loading vs. fuel consumption for the 10-hr (left) and 100-hr (right) fuel classes (tons/acre). esponds to percent black and marker color to pre-burn shrub loading (cooler color = higher load).

In WFEIS, of course, users do not have access to direct measurements of site-level pre-burn loadings, but rely on FCCS fuelbed data. Unfortunately, the location information in the Wright and Pritchard dataset was not detailed enough to produce fuel consumption estimates directly from WFEIS for comparison. This represents a potentially useful future direction.

Table 3 reflects the patterns that can be observed visually in Figure 16. Pre-burn loadings of both 10- and 100-hr fuels are skewed right with distributions that are approximately lognormal. The linear relationship between pre-burn loading and fuel consumption is stronger for 10-hour fuels than for 100-hour fuels, as evidenced by the lower SE associated with 10-hour fuels.

Table 3: Summary statistics for 10-hour and 100-hour Western woody fuel consumption.

	Standard Deviation for Input Variable Sample Values			
Variable	**Mean**	**Range**	**SD**	
10-hour pre-burn loading (tons/acre)	1.43	0.0, 5.9	1.21	
100-hour pre-burn loading (tons/acre)	1.86	0.5, 6.3	1.21	
10-hour fuel consumption (tons/acre)	1.20	0.0, 5.5	1.11	
100-hour fuel consumption	1.33	0.0, 6.0	1.12	
	Standard Error for Regression/Prediction Coefficients			
Coefficient Variable	**Coefficient**	**SE**	**Z**	**Pr(>|z|)**
10-hour pre-burn loading	0.863	0.017	49.7	$< 2e^{-16}$

(tons/acre)				
100-hour pre-burn loading (tons/acre)	0.749	0.029	25.83	$< 2e^{-16}$

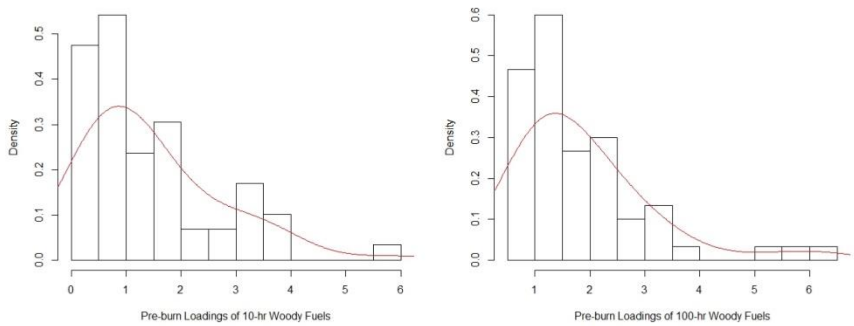


Figure 16: Histograms of sample data for input variables overlaid with kernel density lines. Pre-burn shrub loadings (left) and percent blackened (right) from Wright 2013.

Next, as with shrubs, we can visualize estimated vs. measured fuel consumption slightly differently using confidence intervals. Figure 17 represents the fuel consumption estimates made from measured values of pre-burn loading (purple) with error bars representing the 95% CI (SE*1.96), along with black points representing the measured, or "true", fuel consumption for each fuel class. For both parts of Figure 17, sites are ordered by increasing pre-burn fuel loading for that fuel class. Most of the confidence intervals are fairly narrow, but many of the measured values (black points) fall outside of the intervals. Although the difference between the measured and estimated values are still small (< 1 ton/acre in almost all cases), this begs the question of whether the CONSUME equations could be improved (see Discussion section for followup).

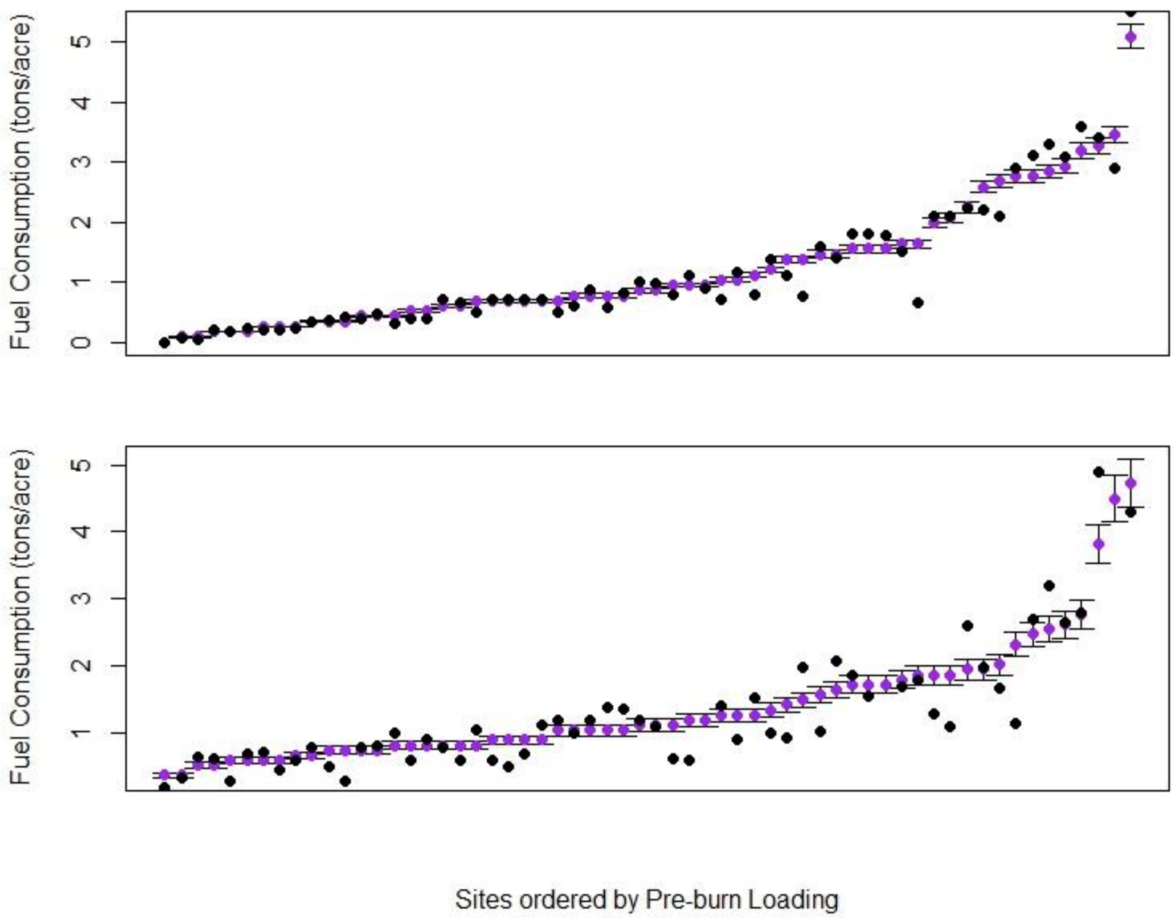


Figure 17: Fitted estimates of proportion of woody fuel loading consumed using measured values of pre-burn loading (purple) and the measured values of fuel loading consumed (black) for 10-hour fuels (top) and 100-hour fuels (bottom). Error bars indicate the 95% confidence interval of the predictions made using measured pre-burn loadings.

FCCS Fuelbed Shrub Loading Values

The next logical step to take is to compare the 60 observations from Ponderosa Pine-dominated western forests used to construct the Western woody fuels equations (Wright & Pritchard 2006b) to the fuel loadings for all FCCS fuelbeds that currently utilize the Western equations. Within CONSUME, the Western woody fuels equations are used for the boreal and western regions (Bailey's ecoregions 120, 130, 210, 220, 240, 250, 260, 330 and 340) (Prichard et al. 2006). Figure shows the extent of the boreal, western and southern regions in North America used by WFEIS to select a CONSUME equation. The western and boreal regions together account for 113 fuelbeds.

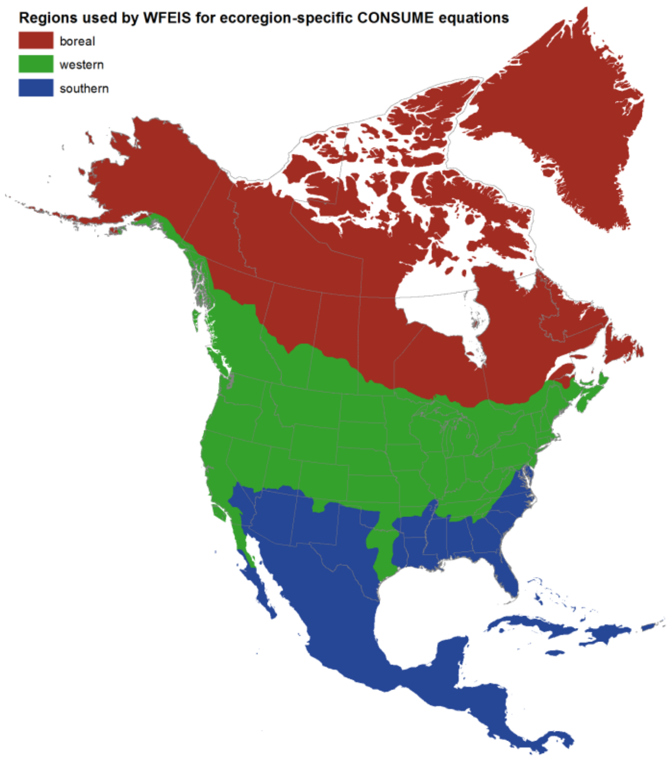


Figure 18: Regions used by WFEIS for CONSUME equation selection.

The probability density plots on the left below (Figure 19) represent the 60 observations used to create the model. Overlaid on the plots are blue density lines representing the 113 FCCS values. The plots on the right are the same illustrations but vice versa. The 60 sample observations range higher than the FCCS set, with maxima of 5.9 and 6.3 tons/acre for 10-hour and 100-hour fuels, respectively, vs. 3.5 and 4.9 for the FCCS set. However, the majority of loadings for both 10-hour and 100-hour fuels fall below 4 tons/acre in both datasets, with a rightward skew to all distributions.

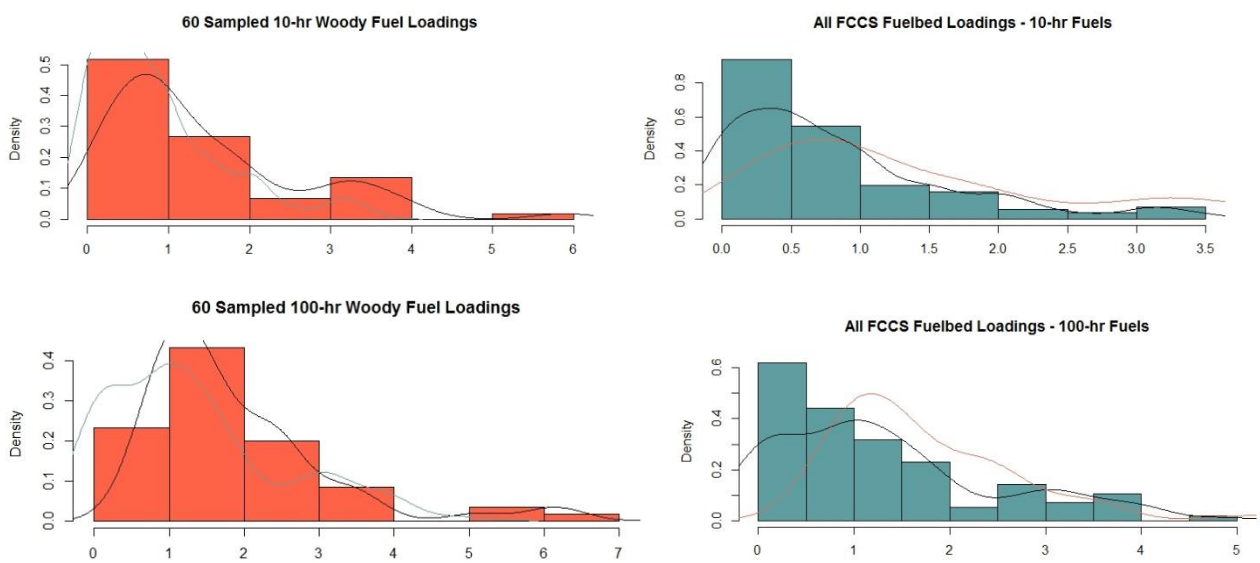


Figure 19: Comparison of woody fuel 10-hr (top) and 100-hr (bottom) loadings for (left) the 60 observations used to parameterize the CONSUME Western woody fuel equations and (right) the 113 FCCS fuelbeds that use the Western woody fuels equations.

Discussion

Additional Sources of Uncertainty

Potential sources of uncertainty in WFEIS estimates fall into several categories. Those examined in this case study include measurement errors in the prescribed fire field data used to develop the CONSUME models, variability resulting from the use of samples rather than censuses, modeling errors due to the inability of CONSUME to fully describe fuel emissions, and the potential for unrepresentative samples. The CONSUME shrub and western woody fuel equations were developed based on a limited number of prescribed fires in big sagebrush landscapes and Ponderosa Pine-dominated forests, respectively. These models are then applied to all shrub and western woody fuels belonging to various taxa.

The implementation of CONSUME in WFEIS introduces new forms of uncertainty. Aside from the WFEIS default value of 50 for $\%b$ for shrub consumption, which has already been described, WFEIS relies on the Fuel Characteristic Classification System (FCCS) to select appropriate fuelbeds. FCCS data provide estimates of the characteristics and amounts of fuels on the landscape. Previous studies of wildland fire emissions have found fuel loading to be the largest error involved in estimating emissions, followed by fuel consumption (Hardy et al. 2001, Peterson 1987, Peterson & Sandberg 1988). The uncertainty of FCCS fuel loadings clearly varies with fuelbed, and the classification system has not been formally tested for performance and accuracy due to the lack of ground data. Furthermore, the 30-m resolution of the LANDFIRE FCCS classification map for the contiguous US includes some spatial error. Keane et al. recently utilized the extensive FIA dataset of plot-level surface fuels to evaluate the classification performance and map accuracy of the FCCS and two other fuel loading classifications, but acknowledge that these data also contain high uncertainty, which had an impact on their evaluation (Keane et al. 2013, Westfall and Woodall 2007). Keane et al. reported a poor classification performance for FCCS compared to measured FIA fuel values for all fuel components, and found that FCCS under-predicted all fuel loadings. When the loadings of the mapped classes for the three evaluated classifications (FCCS, FLM and FTG) were compared to measured FIA fuel loadings, FCCS map accuracy was also poor and was found to have the highest RMSE values (1.46-22.54 vs. 0.66-3.53 for FLM and 0.98-2.42 for FTG). Thus, the accuracy of the FCCS classification used as input data in CONSUME and WFEIS adds considerable, still incompletely characterized uncertainty to model estimates.

In addition to FCCS, WFEIS uses a burned area product (currently MODIS MCD64A1, Landsat MTBS, Landsat Daily, SmartFire 2011 NEI or Agricultural NEI) to select the fire burn perimeter and day of burning used in the WFEIS calculations. These products vary in resolution and performance (Giglio et al. 2009; Eidenshink et al. 2007; Giglio et al. 2006; Loboda and Csiszar 2007; McCarty et al. 2008, 2009; McCarty 2011; Seiler and Crutzen 1980). Although these remote-sensing-based products can account for unburned patches within a burn perimeter, the precision of remote sensing-based methods is limited by sensor resolution and by, e.g., variations in landscape slope, canopy cover and fuel characteristics (French et al. 2004, Sandberg et al. 2002).

Potential Model Improvements

Shrub Consumption

Estimation of shrub consumption is impaired by the current lack of an accurate built-in estimate of area burned (percent black) in WFEIS; the default input is a value of 50%. To identify the best predictor of proportion consumed in the absence of an accurate value for percent black, we compared the current method (2-variable regression with shrub loading and percent black set to 50) to a few alternatives: changing the default for percent black to the mean of the sample values (approx. 60%), using a regression based on shrub loading alone or on percentage live vegetation alone (FCCS fuelbeds include percentage live), or simply using the mean percent consumed from the sample data (56.5%). The results of the comparison relative to the sample data are presented in Table 4. It's clear that the present method can be improved upon, as even using the mean of the sample data to serve directly as proportion consumed is more accurate than using a value of 50. A linear regression based on loading alone also works better than including the default value for percent black and is improved slightly by adding percent live as a second predictor variable.

Table 4: Comparison of estimation methods for proportion of shrub loading consumed.

Method	RMSE (%)
2-variable (loading + %b), %b=50	27.4
2-variable (loading + %b, %b=60	26.3
1-variable (loading)	24.9
1-variable (%live)	26.6
2-variable (loading + %live)	23.8
Mean of sample data	27.0

In addition, two available variables not included in the current model—burn season and dominant shrub species—were evaluated to determine whether they might be informative, but the shrub proportion consumed did not vary significantly among groups for either of these (Figure 20).

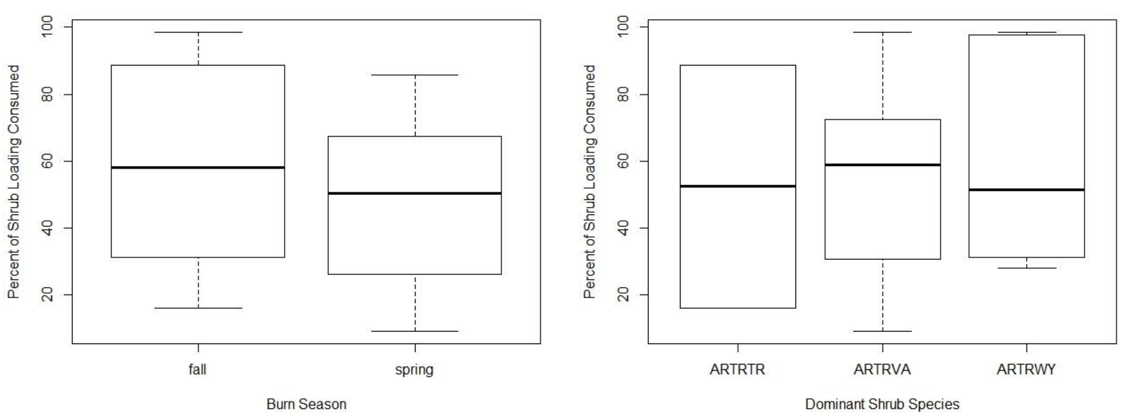


Figure 20: Comparison of sample values of proportion consumed grouped by burn season (left) and dominant shrub species (right).

Western Woody Fuels Consumption

The 10- and 100-hour fuel classes, though they represent small-sized fuels, represent a significant proportion of total woody fuels (24.4±11.9% in the Ponderosa Pine dataset from Wright and Prichard 2006b). One possible method for improving on the CONSUME linear regressions that predict consumption of 10-hour and 100-hour woody fuels as a function of pre-burn loadings would be to add fuel-class-specific fuel moisture as a predictor variable. Because 10-hour and 100-hour fuel moisture are included in the Wright & Prichard 2006b dataset, we can examine the effect of this addition. When woody fuel consumption was modeled as a function of pre-burn loading + fuel moisture with an intercept of 0, fuel moisture was not significant in either the 10-hour ($p = 0.251$) or the 100-hour model ($p = 0.351$). This indicates that fuel moisture is not a useful addition for these fuel classes, supporting its absence from the equations used to estimate their consumption.

Conclusions

For estimating shrub consumption, the binomial link logistic regression model works well. The effects of fitting the logistic model using other combinations of input variables and of using a default value for percent black were explored. This model produces accurate predictions given that the user can estimate the post percent black value within a reasonable margin. If the user knows that over 85% of the shrubs were blackened, in general, it is best to overestimate the percentage. The model performance was lowest when the true percent black value was very high, above that 85% cutoff. Otherwise, the predicted values fall with one or two standard errors of the measured value.

The shrub consumption uncertainty analysis was performed on data from a specific vegetation type (western sagebrush) to predict consumption. The next step would be to apply this model to another shrub dataset for which measured percent black, percent live and proportion consumed data are available to determine how well the model performs. This analysis can then be used as a pathway into a larger, full-fledged analysis where each stratum in CONSUME is analyzed.

An important future action for both the shrub and woody fuel strata will be to obtain detailed location information for the source data so that the measured data can be compared to the results a user would obtain from WFEIS. To partition that uncertainty into its various sources, further studies of the subcomponents of WFEIS, e.g. the burned area products, FCCS fuelbeds, and the performances of other CONSUME equations, will be needed.

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