CSIRO PUBLISHING

*International Journal of Wildland Fire*
https://doi.org/10.1071/WF19160

# Quantifying how sources of uncertainty in combustible biomass propagate to prediction of wildland fire emissions

*Maureen C. Kennedy* [A,D], *Susan J. Prichard* [B], *Donald McKenzie* [B] *and Nancy H. F. French* [C]

[A]School of Interdisciplinary Arts and Sciences, Division of Sciences and Mathematics, University of Washington, 1900 Commerce Street, Tacoma, WA 98402, USA.
[B]School of Environmental and Forest Sciences, University of Washington, Box 352100, Seattle, WA 98195-2100, USA.
[C]Michigan Tech Research Institute, Michigan Technological University, 3600 Green Court, Suite 100, Ann Arbor, MI 48105, USA.
[D]Corresponding author. Email: mkenn@uw.edu

**Abstract.** Smoke emissions from wildland fires contribute to concentrations of atmospheric particulate matter and greenhouse gases, influencing public health and climate. Prediction of emissions is critical for smoke management to mitigate the effects on visibility and air quality. Models that predict emissions require estimates of the amount of combustible biomass. When measurements are unavailable, fuel maps may be used to define the inputs for models. Mapped products are based on averages that poorly represent the inherent variability of wildland fuels, but that variability is an important source of uncertainty in predicting emissions. We evaluated the sensitivity of emissions estimates to wildland fuel biomass variability using two models commonly used to predict emissions: Consume and the First Order Fire Effects Model (FOFEM). Flaming emissions were consistently most sensitive to litter loading (Sobol index 0.426–0.742). Smouldering emissions were most often sensitive to duff loading (Sobol 0.655–0.704) under the extreme environmental scenario. Under the moderate environmental scenario, FOFEM-predicted smouldering emissions were similarly sensitive to sound and rotten coarse woody debris (CWD) and duff fuel components (Sobol 0.193–0.376). High variability in loading propagated to wide prediction intervals for emissions. Direct measurements of litter, duff and coarse wood should be prioritised to reduce overall uncertainty.

**Additional keywords:** prediction interval, sensitivity analysis, uncertainty analysis.

Received 4 October 2019, accepted 14 May 2020, published online 16 June 2020

## Introduction

Smoke emissions from wildland fires are major contributors to greenhouse gases and other air pollutants, with associated effects on radiative forcing of climate and public health (Bowman *et al.* 2009; Liu *et al.* 2014, 2015; Reid *et al.* 2016; Cascio 2018; Fann *et al.* 2018). Anthropogenic burning in grassland and savanna landscapes throughout the world is also a major source of pollutant emissions (Pereira 2003; Shi *et al.* 2015). Recent trends in wildfire area burned vary globally, with increases in many regions (Riaño *et al.* 2007; Flannigan *et al.* 2009; Giglio *et al.* 2013), particularly those with closed-canopy forests (Riaño *et al.* 2007), and declines in other regions. These regional differences depend on how environmental controls affect vegetation and combustibility (Littell *et al.* 2018; Forkel *et al.* 2019). In some vegetation types the area burned is expected to continue to increase (Abatzoglou and Williams 2016; Littell *et al.* 2018) and contribute to increases in pollutant emissions.

Forest management in some regions aims to reduce fuels that are available for combustion and thereby mitigate wildfire severity (Kalies and Yocom Kent 2016). Fuel reduction treatments, including thinning and prescribed burning, are implemented under various policy and regulatory frameworks (Collins *et al.* 2010). Although prescribed fires may mitigate wildfire severity, they may also reduce air quality, one of the barriers to increasing the pace and scale of such treatments (Quinn-Davidson and Varner 2012; Ryan *et al.* 2013). Forest management using prescribed fire requires credible estimates of emissions from burn prescriptions and ways to inform smoke reduction techniques (Peterson *et al.* 2018). In addition, understanding the trade-offs between prescribed burning programs and potential wildfires is also important for local and regional planning.

Quantification of uncertainty is critical to ensure that managers have reliable predictions. This includes accounting for uncertainty in fuel consumption and emissions predictions resulting from model input errors. To date, however, predictions of emissions rarely include estimates of uncertainty. Four types of uncertainty affect predictions from any model: uncertainty in data inputs (e.g. imperfect measurements, natural variation and classification assumptions), model structure, estimates of parameters and irreducible natural stochasticity (Beck 1987; O'Neill and Gardner 1979; Turley and Ford 2009). To predict fuel consumption and emissions from wildland and prescribed fires, data inputs include area burned, amount of combustible biomass (hereafter termed 'fuel loading') and environmental conditions (Ottmar 2014). Model structure and estimated parameters are also sources of uncertainty in predictions. For example, two fuel consumption models in use today, Consume (Ottmar 2014) and the First Order Fire Effects Model (FOFEM; Reinhardt 2003), combine empirical and physical ('process-based') calculations of consumption. Total emissions are a product of consumed fuel in each phase of combustion (smouldering or flaming) and an emissions factor. Emissions factors partition emissions into gas species (e.g. carbon dioxide, carbon monoxide and other trace gases) and particulates. Emissions factors are estimated empirically, from experiments or remote sensing, with the inherent uncertainty of such observations (Urbanski 2014; Prichard *et al.* 2020).

Fuel loading is recognised as a fundamentally important source of uncertainty for predicting smoke emissions from wildland fire (Larkin *et al.* 2009; Drury *et al.* 2014), but is often challenging to measure consistently and accurately (Keane 2015). Monte Carlo methods can estimate the sensitivity of emissions estimates to different model inputs and settings (French *et al.* 2004; Urbanski *et al.* 2011), but they require sampling from a plausible distribution of the variables of interest. Urbanski *et al.* (2011) recommended drawing from distributions of fuel loading estimated from real data to ensure that analyses result in plausible distributions, which is the purpose of this study.

Direct measures of fuel loading are rarely available before a wildland fire. Studies of emissions often rely on generalised fuel classifications, such as the Fuels Characterisation and Classification system (FCCS; McKenzie *et al.* 2012) or fuel loading models (Lutes *et al.* 2009), which are assigned and mapped based on vegetation classifications. Mapped estimates give average values of fuel loadings for the associated fuel class at a given location, but that value is unlikely to be the actual loading that is present in a particular time or place, because fuel loadings are highly dynamic and as a result, highly variable (Keane *et al.* 2013). If fuel loadings are estimated indirectly, using a single value provides false precision for estimates of emissions, thereby masking the variability in fuel loading values associated with a given vegetation type (Prichard *et al.* 2019). The consequences of this variability in fuel loading for predicting smoke emissions are not well understood.

For the recently created North American Wildland Fuel Database (NAWFD), Prichard *et al.* (2019) compiled existing sources of measured fuel loadings aggregated by major existing vegetation groups (EVGs), a coarse classification of vegetation types in the USA provided by the LANDFIRE project (Rollins 2009). They used this database to estimate empirical distribution functions for the loadings of different fuel components. The distributions were characterised by mean values, variability and distribution shape. This large dataset enabled us to predict consequences for emissions prediction of the variability in fuels. Here we used sensitivity and uncertainty analysis to quantify how variability in the fuel loading inputs, by EVG, propagates to the emissions predicted by models. This is a prerequisite for using models to make robust predictions of emissions for specific applications, such as prescribed burn planning. In our view, robust predictions should include estimates of uncertainty in fuel loadings and estimates of the effects of that uncertainty on emissions.

Uncertainty analysis quantifies the uncertainty in model predictions given underlying uncertainty in data inputs or parameter values (Jansen 1998). Sensitivity analysis (Cariboni *et al.* 2007) is concerned with quantifying the influence of model inputs and parameters on target model outputs, such as the prediction of particulate emissions. If a small change in a particular fuel component (e.g. shrub, herb or downed wood) produces relatively large changes to predicted emissions, then the model is judged to be sensitive to that input. Using this method we can rank fuel loading components by the relative sensitivity of model outputs.

The overarching goal is to improve understanding of the variability in wildland fuels, and the consequences for prediction of emissions, and thereby to direct resources to efforts that will best reduce uncertainty in smoke predictions. Using the NAWFD, we evaluated the contribution of uncertainty in fuel loading inputs to the sensitivity and uncertainty in predicted wildfire emissions using a global sensitivity analysis (Cariboni *et al.* 2007; Saltelli *et al.* 2010). Our specific objectives were as follows.

1. Identify fuel components that most influenced the prediction of emissions in both the flaming and smouldering phases of combustion.
2. Assess whether sensitivity to fuel loading changed with environmental conditions or with the choice of model to predict emissions.
3. Understand how variability in fuel loading quantified by (Prichard *et al.* 2019) propagated to uncertainty in predicted emissions in both the flaming and smouldering phases of combustion.

We addressed these objectives with two operational fuel consumption models (Consume and FOFEM), for several representative North American fuel types. An overview of the analysis using these two models is given in Fig. 1.

## Methods

### *Consume and FOFEM descriptions*

Consume 5.0 predicts total fuel consumption and combustion by phase (flaming, smouldering and residual smouldering), with statistical models estimated from prescribed burn studies in south-eastern pine, western ponderosa pine, western grasslands and western shrublands (Ottmar *et al.* 2006; McIver and Ottmar 2007; Wright 2013*a*, 2013*b*; Prichard *et al.* 2017). Because the majority of these datasets were sampled from prescribed fires, source data do not represent the wide range of wildland fire conditions. These conditions include fuel moisture (which can change over hours and weeks) and day-of-burn environmental variables and weather such as wind speed and relative humidity. The empirically developed relationships in Consume predict consumption of woody components as a consistent proportion of the fuel loading present. Shrub consumption is not modelled in

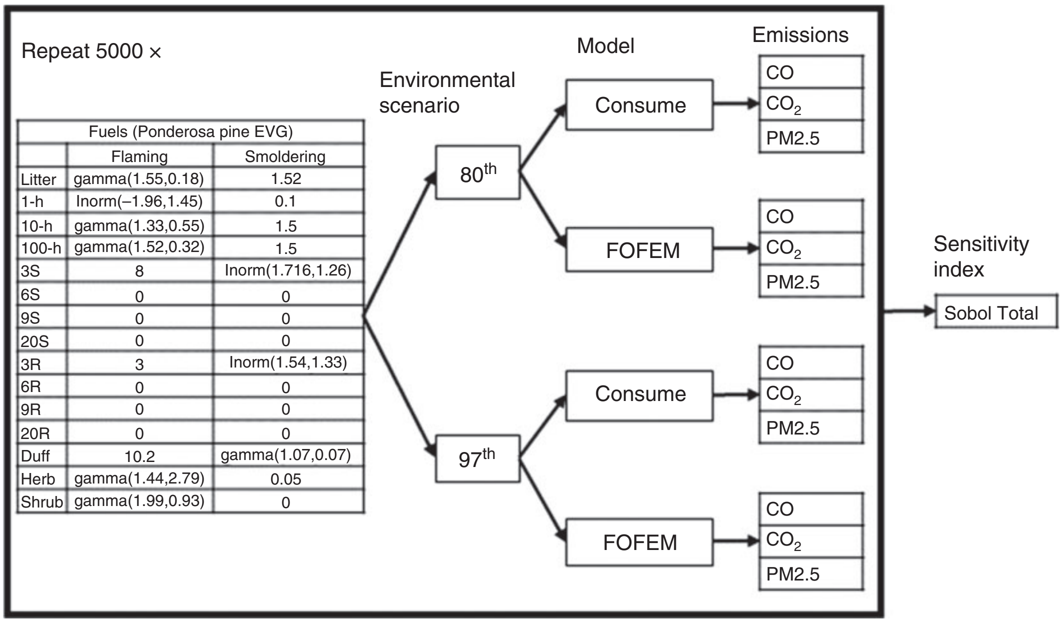


**Fig. 1.** Diagram illustrating the sensitivity analysis method. Fuel loading combinations are generated as combinations of random draws from a set of fuel layers and constant baseline values that differ by existing vegetation group (EVG). Analysis is conducted separately for flaming and smouldering emissions (flaming example pictured for the ponderosa pine EVG). Random draws are either from a lognormal (lnorm) or gamma distribution. For each fuel combination simulations are run using Consume and First Order Fire Effects Model (FOFEM) in both moderate (80th percentile) and extreme (97th percentile) environmental scenarios. Emission predictions for CO, $CO_2$ and PM2.5 are recorded and repeated for 5000 random draws. For each set of model predictions the sensitivity indices are calculated.

Consume; rather it is prescribed by the user as a percent of the area affected.

FOFEM 6.4 predicts fuel consumption and emissions together with tree mortality and soil heating (Reinhardt 2003; Lutes 2017). It uses a mix of consumption models that depends on fuel type and location. These include empirical equations, the BURNUP physical process module that predicts heat transfer and burning rates of woody fuel by size class (Albini and Reinhardt 1995, 1997) and default assumptions based on fuel component, season and the region of the USA. BURNUP estimates consumption of larger fuels in part from interactions with smaller fuels and the estimated intensity of burning is used to differentiate the smouldering from flaming phases of combustion. A given loading of larger fuels can be consumed at different rates depending on its interactions with smaller fuels, resulting in variable consumption for a given fuel. Duff consumption is modelled using empirical equations selected by region and duff moisture assessment, except for chaparral types where 100% consumption is assumed. Litter consumption is typically modelled in the BURNUP physical process model, which tends to predict 100% consumption. A default assumption is used in the south-east USA. Fine and coarse wood consumption is always modelled in BURNUP. FOFEM typically assumes 100% or 90% herbaceous fuel consumption based on season, but empirical equations are used when the south-east region is selected. Shrub consumption is typically assumed to be 50–90% based on cover type and season, but empirical equations are used for non-pocosin shrubs (Hough 1978) or flatwoods (Wright 2013*b*) in the south-east USA.

For both models, wildland fire emissions of gases and particulates are calculated with emissions factors, empirically derived scalar values multiplied by the consumed fuels for different emission components. For example, Consume uses emissions factors recently summarised from the Smoke Emissions Repository Application (Prichard *et al.* 2020). For a given amount of consumed fuel the emissions may be higher or lower depending on the chosen emissions factor, which themselves have uncertainty (Prichard *et al.* 2020). Given that our focus was on how the variability of fuels propagates to uncertainty in emissions prediction, and that the emissions factor affects the magnitude but not the variability in emissions, we chose to apply a common emissions factor to calculate emissions for both models. From Prichard *et al.* (2020), we used the western forest emissions factor for all EVGs, with the exception of the Beech, maple, basswood EVG (Table 1). Note also that these models are continually being updated, so direct model comparisons pertain to the versions under study.

### *Test-case vegetation groups, fuel components and baseline loadings*

For this analysis, we focused on three candidate EVGs for the flaming phase of combustion and three candidate EVGs for the smouldering phase of combustion. (Table 1; one EVG was common between the two fuel groups). These were chosen because (1) they represent major fire-prone vegetation groups in continental USA, (2) they have potential internal variation in fuel loadings and (3) they had sufficient coverage of target fuel loading components in the database (> 30 complete cases for

**Table 1. Environmental scenarios for each existing vegetation group (EVG)**

Each EVG name and corresponding numerical identifier (in parentheses) is given. For duff fuel moisture (FM), 1000-h fuel moisture, percent burned, percent shrub black and litter FM the 80th percentile scenario value is given first, then the 97th percentile scenario value (80th/97th). For region the Consume ecoregion is given first and the FOFEM region given second (Consume/FOFEM). Emissions factors (EF) are taken from Prichard *et al.* (2020) and are scaled as Mg emissions per Mg consumed fuels. FOFEM, First Order Fire Effects Model

| EVG | | Douglas fir, ponderosa pine, lodgepole pine forest (625) | Ponderosa pine forest (631) | Beech, maple, basswood (625) | Lodgepole pine forest and woodland (622) | Spruce-fir forest and woodland (639) |
|---|---|---|---|---|---|---|
| Duff FM | 80th | 30 | 30 | 30 | 30 | 30 |
| (%) | 97th | 20 | 20 | 20 | 20 | 20 |
| 1000-h | 80th | 30 | 30 | 30 | 30 | 30 |
| FM (%) | 97th | 5 | 5 | 5 | 5 | 5 |
| % Burn | 80th | 20 | 20 | 20 | 20 | 20 |
| | 97th | 50 | 50 | 50 | 50 | 50 |
| % Shrub | 80th | 80 | 80 | 80 | 80 | 80 |
| black | 97th | 100 | 100 | 100 | 100 | 100 |
| Litter FM | 80th | 6 | 6 | 6 | 6 | 6 |
| (%) | 97th | 4 | 4 | 4 | 4 | 4 |
| Region | Consume | Western | Western | Southern | Western | Western |
| | FOFEM | Interior West | Interior West | South East | Interior West | Pacific West |
| Season | | Summer | Summer | Summer | Summer | Summer |
| EF PM2.5 | | 0.0143 | 0.0143 | 0.01478 | 0.0143 | 0.0143 |
| EF $CO_2$ | | 1.58788 | 1.58788 | 1.6505 | 1.58788 | 1.58788 |
| EF CO | | 0.09793 | 0.09793 | 0.08419 | 0.09793 | 0.09793 |

the target fuel loading components). The EVGs chosen for this study were forested types because forestlands have much greater coverage in the NAWFD than either shrublands or grasslands.

A wildland fuelbed has numerous components that contribute to emissions. Rather than consider all fuelbed components simultaneously, we performed the analysis separately for fuels that dominate flaming combustion (fine wood, shrubs, herbs and litter; Ottmar 2014; hereafter termed 'flaming fuels') and those that dominate smouldering combustion (sound coarse woody debris (CWD), rotten CWD and duff, Ottmar 2014; hereafter termed 'smouldering fuels'). We varied the flaming fuel components for the first analysis and the smouldering components for the second analysis. The fuel loading components that we varied did not represent all fuel components used to calculate emissions. We selected baseline loading values for the remaining fuel components for each EVG based on a representative FCCS fuelbed (Table 2). Consume has more fuel components for calculating emissions than FOFEM, so the models were standardised by giving baseline values of zero in the Consume input file for fuel components included in Consume and not in FOFEM.

### *Quantifying distributions of fuel loading*

The NAWFD estimates empirical distributions for each fuel loading component with sufficient data for distribution fitting (Prichard *et al.* 2019). The database allowed us to identify both the expected loading and the associated variability for a given vegetation group. Without other information, such as direct measure measurement, fuel loadings at a particular place in the landscape may be considered a random draw from the distribution associated with its vegetation classification. Here we sampled from the empirical distributions estimated in Prichard *et al.* (2019), for either flaming or smouldering fuels, for each of the EVGs selected for the corresponding analysis. Methods for distribution estimation are described in Prichard *et al.* (2019) and in the Supplementary Material online.

### *Correlation matrix*

It is possible that fuel loading components correlate with each other. For example, with a positive correlation, when a low value of 10-h loading is observed it is likely that 100-h loading is also relatively low. We estimated a Spearman rank correlation matrix for each set of fuel type (e.g. flaming or smouldering fuels) for each EVG. This gave pairwise correlations among the fuel components, with a value near 1 indicating a strong positive correlation. A value near zero indicates no correlation. We then adapted the matrix-based methodology of Iman and Conover (1982) to mimic the empirical rank correlation structure in the sampled values. Methods for estimation of the correlation matrix are given in the Supplementary Material online. The result of the sampling procedure was a matrix of 5000 random combinations of smouldering or flaming fuels for each EVG (Fig. 1), with a correlation structure that matched the estimate for each set of fuel types for each EVG.

### *Target outputs and environmental variable settings*

Effects of fuel loading on emissions prediction were assessed for three common air pollutants: PM2.5, $CO_2$ and CO. For sensitivity analysis, we only considered either the flaming or smouldering phase emissions, whereas we calculated total emissions (flaming and smouldering) for our analysis of how variability propagated to emissions. We applied two different environmental scenarios for each random sample of fuel loading values. These approximated extreme hazardous conditions (97th percentile) and moderate conditions (80th percentile) for each EVG (Table 1). Such scenarios are commonly used in wildland fire management planning.

**Table 2. Mean fuel loadings (with standard deviations given in parentheses), defined as dry weight biomass in Mg ha$^{-1}$, for each existing vegetation group (EVG)**

Baseline values are given for the fuels not included in the analysis. The proportion of zero loadings is given below the mean values in parentheses. RCWD, rotten coarse woody debris; SCWD, sound coarse woody debris

| EVG | Douglas fir, ponderosa pine, lodgepole pine forest (625) | Ponderosa pine forest (631) | Beech, maple, basswood (655) | Lodgepole pine forest and woodland (622) | Ponderosa pine forest (631) | Spruce-fir forest and woodland (639) |
|---|---|---|---|---|---|---|
| 1 h | 0.75 (0.72) [0.04] | 0.38 (0.99) [0.08] | 0.13 (0.10) [0.01] | 0.90 | 0.22 | 1.12 |
| 10 h | 3.23 (2.65) [0.01] | 2.42 (2.17) [0.02] | 1.31 (0.88) [0.02] | 4.93 | 3.36 | 2.24 |
| 100 h | 5.86 (4.75) [0.06] | 4.21 (3.91) [0.12] | 4.22 (4.14) [0.12] | 6.27 | 3.36 | 4.48 |
| Herb | 0.37 (0.32) [0.01] | 0.50 (0.43) [0.01] | 0.53 (0.44) [0.03] | 0.45 | 0.11 | 0.67 |
| Litter | 10.35 (8.32) [0.01] | 8.61 (7.11) [0.003] | 9.91 (5.75) [0.02] | 1.67 | 3.41 | 0.73 |
| Shrub | 2.08 (2.02) [0.02] | 1.95 (1.57) [0.10] | 1.60 (1.38) [0.12] | 0.00 | 0.00 | 6.42 |
| SCWD | 0.90 | 17.92 | 6.72 | 9.39 (25.92) [0.20] | 7.56 (19.07) [0.37] | 15.17 (20.68) [0.21] |
| RCWD | 0.90 | 6.72 | 1.12 | 9.28 (13.53) [0.31] | 5.19 (14.35) [0.49] | 17.26 (22.28) [0.39] |
| Duff | 16.76 | 22.85 | 16.13 | 20.83 (17.81) [0.03] | 14.22 (14.28) [0.04] | 23.77 (19.46) [0.01] |

From the set of sampled fuel loadings and environmental inputs we created an input file suitable for each model. Any randomly sampled value $< 0.001$ was given a value of zero, with the exception of duff. Any randomly generated value $< 0.1$ for duff was given the minimum allowed value of 0.1 for input to both models. Sound and rotten CWD represent total large fuels ($\geq$ 1000-h size class). In FOFEM and Consume, large fuels are partitioned into 1000-h, 10000-h and $>$ 10 000-h size classes. To simplify comparisons, we placed the sound and rotten CWD loading values into the 1000-h size class for both models.

We then used each model to estimate fuel consumption and emissions for each fuel loading combination in the input file, for each environmental scenario (80th and 97th percentiles). These were then used in the sensitivity and uncertainty analyses (Fig. 1).

## *Sensitivity analysis*

To identify fuel components with the largest effect on emissions estimates, we used Sobol variance partitioning (Sobol' 2001). This method of global sensitivity analysis quantifies, in this case, the contribution of the variability in data inputs to the total variability in model predictions (Saltelli *et al.* 2010). This index includes interactions with other inputs. Details of the estimation of the sensitivity index are given in Supplementary Material online. A higher value of the sensitivity index indicates that the model prediction was more sensitive to that output.

## *Quantifying uncertainty propagation*

To understand how variability in fuel loading propagates to variability in consumed fuels, we quantified the variance and standard deviation of both the fuel loading and the consumed fuels. For a given fuel component the variance was quantified as the sum of squared deviations from the mean value divided by $N$– 1 ($N = 5000$). For example, if 1-h fuels are represented by $X$ and $\overline{X}$ is the mean value for 1-h fuels for a given EVG, then the variance in 1-h fuel loading is represented by:

$$\frac{\sum_{i=1}^{N}\left(X_i - \overline{X}\right)^2}{N-1} \tag{1}$$

The variance was calculated for each fuel component individually and for the total fuels (the sum of fuels across all fuel components). The standard deviation was calculated as the square root of this value.

Each model predicts a proportion of the fuel loading that is consumed. For each fuel component, the amount of consumed fuels is that proportion multiplied by the fuel loading. The total consumed fuel is then the sum of the consumed fuels across all fuel components. The loading for each fuel component is a random variable ($X_i$) and there are $k$ fuel components under consideration. For example, in our flaming fuels analysis we evaluated six fuel types ($X_1, X_2, X_3, X_4, X_5, X_6$), which resulted in six different random variables ($k = 6$). If we assume a constant proportion of fuels consumed ($p_i$ for each fuel component), then the total consumed fuels can be written as:

$$p_1X_1 + p_2X_2 + p_3X_3 + p_4X_4 + p_5X_5 + p_6X_6 = \sum_{i=1}^{k} p_iX_i \tag{2}$$

The variance of total consumed fuels is the variance of this sum of random variables. However, due to the properties of the variance, this is not just a simple sum. We have to consider both the value $p_i$ as well as whether the variables correlate with each other.

In general, the variance ($V$) of the sum of multiple random variables is:

$$V\left(\sum_{i=1}^{k} p_i X_i\right) = \sum_{i=1}^{k}\sum_{j=1}^{k} p_i p_j Cov\left(X_i X_j\right), \tag{3}$$

where $Cov$ refers to the covariance between two random variables. The covariance is a measure of how two random variables vary together and is related to the correlation coefficient. A higher covariance corresponds to a higher correlation. If two random variables are uncorrelated then their covariance is 0. The $Cov(X_i X_i) = V(X_i)$.

For example, if $k = 2$, then:

$$V(p_1 X_1 + p_2 X_2) = p_1^2 V(X_1) + p_2^2 V(X_2) + 2p_1 p_2 Cov(X_1 X_2) \tag{4}$$

Each proportion ($p_i$) is $\leq$1. Therefore, if the fuels are uncorrelated ($Cov = 0$), then the variance of the sum will be less than or equal to the sum of the variances. If the fuel components are strongly correlated, then it is possible for the variance of the sum to be greater than the sum of the individual variances. That would mean that the variability in the total consumed fuels could be higher than the variability of the total fuel loading.

The value of proportion consumed ($p_i$) also determines how the variability propagates from fuel loading to consumed fuels (Eqn 3). We calculated the proportion of fuel loading consumed, for each sampled fuel component, for each model. Higher values of proportion consumed increase variability in consumed fuels for a given loading. Furthermore, if for a given model structure the proportion of consumed fuels is not constant with fuel loading, then this too can result in the variability in the total consumed fuels exceeding the variability in the total fuel loading.

We compared variability in consumed fuels to variability in fuel loading by taking a percentage. In general, if the percentage variability was 0%, then none of the variability in loading propagated to variability in consumed fuels. A percentage variability of 100% indicated that all of the variability in loading propagated to variability in consumed fuels. For total consumed fuels, a value > 100% indicates that there was greater variability in total consumed fuels than in the total fuel loading.

We then calculated 95% prediction intervals as the middle 95% of predicted emissions for each model (the 0.025 and 0.975 quantile values). Such intervals communicate plausible ranges of emissions given the underlying variability in fuel loading. These intervals were created for both environmental scenarios and for both models.

**Table 3. Pairwise Spearman rank correlation values for each pair of fuel loading components, by flaming or smouldering fuels and by existing vegetation group (EVG)**

A value near zero indicates no relationship between the fuel loading components, a value near 1 indicates a perfect relationship between the fuel loading components. RCWD, rotten coarse woody debris; SCWD, sound coarse woody debris

| | EVG | Douglas fir, ponderosa pine, lodgepole pine forest (625) | Ponderosa pine forest (631) | Beech, maple, basswood (655) |
|---|---|---|---|---|
| Flaming fuel loading pair | 1-h, 10-h | 0.481 | 0.492 | 0.523 |
| | 1-h, 100-h | 0.195 | 0.246 | 0.345 |
| | 1-h, herb | −0.087 | −0.24 | −0.192 |
| | 1-h,litter | 0.595 | 0.144 | −0.086 |
| | 1-h, shrub | 0.041 | 0.266 | 0.069 |
| | 10-h, 100-h | 0.537 | 0.448 | 0.475 |
| | 10-h, herb | 0.02 | −0.144 | −0.123 |
| | 10-h,litter | 0.407 | 0.331 | −0.157 |
| | 10-h, shrub | 0.031 | 0.063 | 0.171 |
| | 100-h, herb | 0.2 | −0.037 | −0.238 |
| | 100-h,litter | 0.277 | 0.31 | −0.122 |
| | 100-h, shrub | 0.152 | 0.066 | 0.02 |
| | herb, litter | −0.03 | −0.078 | −0.099 |
| | herb, shrub | 0.081 | 0.06 | 0.215 |
| | litter, shrub | 0.097 | 0.076 | −0.028 |
| | EVG | Lodgepole pine forest and woodland (622) | Ponderosa pine forest (631) | Spruce-fir forest and woodland (639) |
| Smouldering fuel loading pair | SCWD, RCWD | 0.171 | 0.176 | 0.29 |
| | SCWD, duff | 0.206 | 0.197 | 0.295 |
| | RCWD, duff | −0.126 | 0.233 | 0.214 |

## Results

### *Quantifying the distributions of fuel loading*

Standard deviations for flaming fuel loadings ranged from as low as 0.1 Mg ha$^{-1}$ for 1-h fuels to 8.37 Mg ha$^{-1}$ for litter fuels (Figs S1, S2 in the Supplementary Material online; Table 2). The highest standard deviations were associated with litter fuels regardless of EVG. Overall, standard deviations were close to or even exceeded the mean values. The proportion of zero values (i.e. the fuel component was not present) was generally low for flaming fuels, ranging from 1% to 12%. Correlations in fuel loading among pairs of flaming fuel components ranged from 0.03 to 0.54 depending on pairing (Table 3).

Standard deviations for smouldering fuel loadings ranged from 13.5 Mg ha$^{-1}$ to 25.9 Mg ha$^{-1}$, with the highest values depending on EVG (Table 2). For the lodgepole pine forest and woodland and the ponderosa pine forest EVGs, sound CWD had the highest standard deviation. For the spruce-fir forest and woodland EVG, rotten CWD had the highest standard deviation. Overall variability for smouldering fuels was high, with standard deviations near or exceeding the mean values. The proportions of zero values (the fuel component was not present) was higher for smouldering than flaming fuels, ranging from 1% to 49%. Correlations in fuel loading among pairs of smouldering fuel components overall were lower than those among flaming fuel loadings, ranging between 0.17 and 0.30 (Table 3).

### *Sensitivity analysis*

The sensitivity of flaming-phase emissions to fuels that contribute most to flaming combustion (1-, 10-, 100-h, herb, litter, shrub) was consistent across model type, environmental scenario and baseline EVG. Flaming-phase emissions were most sensitive to litter loading, with strong to moderate sensitivity to the 10- and 100-h loading (Fig. 2*a*).

Sensitivity of smouldering phase emissions to coarse wood and duff layers differed between Consume and FOFEM and also by baseline EVG and environmental scenario. For the 97th percentile environmental scenario, smouldering phase emissions were consistently most sensitive to duff loading (Fig. 2*b*). There were differences in sensitivity under the 80th percentile environmental scenario; FOFEM smouldering emissions sensitivity in the spruce-fir forest EVG was higher for rotten CWD than duff and in the remaining two EVGs rotten wood and duff sensitivities were similar (Fig. 2*b*).

### *Quantifying uncertainty propagation (flaming)*

There were notable differences between the two models in how variability propagated from fuel loading to consumed fuels. For Consume, total consumed fuels had less variability than flaming fuel loading (Table 4; 42–53%). In contrast, the variability in total consumed fuels was as low as 57% and as high as 123% of the variability in total flaming fuel loading when FOFEM was used to predict emissions (Table 5). Variability in consumed fuels that is greater than the variability in the fuel loading can be explained in part by the correlation structure of the flaming fuels (with moderate correlations in the fine fuels; Table 3; Eqn 3), but also by the proportion consumed (Fig. 3).

For Consume, the proportion of loading consumed for the different fuel components was consistent with fuel loading (Fig. 3; Fig. S3) and generally lower than the proportion consumed for FOFEM. In the flaming fuels analysis, when values of smouldering fuel loadings were held fixed, Consume predicted a constant proportion consumed. In contrast, the proportion consumed of smouldering fuels in FOFEM differed even when the smouldering fuel loading itself was held constant (Fig. 3*b*). This is because the consumption of the larger fuels depends on interactions with the smaller fuels in the BURNUP process model. For a given CWD fuel loading, the consumption differed depending on the loading of the flaming fuels.

For a given emissions factor, the variability in consumed fuels related to the width of 95% prediction intervals in emissions. FOFEM had greater variability in consumed fuels for a given fuel loading (Tables 4, 5), leading to prediction intervals with similar lower bounds but higher upper bounds than those for Consume (Fig. 4*a*; Table S2 in Supplementary Material online).

### *Quantifying uncertainty propagation (smouldering)*

For both models, the variability in total consumed fuels was less than the variability in total smouldering fuel loading (Table 6). For a given fuel loading, the variability in consumed fuels was lower for Consume (21–26% of the variability in fuel loading) than for FOFEM (86–89% of the variability in fuel loading). This means that in the FOFEM model more of the variability in total loading of smouldering fuels propagated to the variability in consumed fuels than in the Consume model. These percentages in general were also less for smouldering fuels than they were for flaming fuels (Tables 4–6). Differences between the models can be accounted for in part by differences in the proportion consumed for a given fuel loading.

The proportion consumed in smouldering fuels was consistent for Consume regardless of fuel loading and between environmental scenarios (Fig. 3*b*; Fig. S3). For FOFEM, the proportion consumed was highly variable and increased with increasing fuel loading. This was due to the BURNUP process model structure, where the burning of smaller fuels increased intensity and the consumption of larger fuels and higher loading increased consumption overall. This in turn led to greater variability in the amount of consumed fuels and to wider prediction intervals for emissions.

For a given emissions factor, the higher variability in consumed fuels resulted in higher and more variable predicted emissions for FOFEM than for Consume (Fig. 4*b*). For example, for the lodgepole pine forest and woodland EVG, the prediction interval for CO emissions predicted by Consume ranged from 18.87 to 116.72 Mg $ha^{-1}$. The prediction interval for CO emissions predicted by FOFEM ranged from 24.1 to 193.22 Mg $ha^{-1}$ (Table S3). Both the lower and upper bounds for the FOFEM prediction interval were higher than for the Consume prediction interval. These prediction intervals were wider than those associated with flaming fuels (Fig. 4).

## Discussion

In our analysis there were two main outcomes that we consider in further detail below.

1. Given the underlying variability in fuel loading, flaming emissions were most sensitive to litter loading and smouldering emissions were most sensitive to duff and coarse wood loading.
2. Variability in fuel loading propagated to high uncertainty in corresponding emissions estimates, but uncertainty differed by model structure.

The flaming phase of emissions (e.g. from shrubs, herbs, fine wood and litter) was most sensitive to litter loading (Fig. 2*a*), regardless of emission model. Among the flaming fuels, litter loading also had the highest variability. Both models predict relatively high consumption of flaming fuels, with little variability in the proportion consumed (Fig. 3*a*). Consequently, variability in consumed fuels was more directly related to variability in fuel loading. A loading component with more variability would therefore contribute more to the total variability in consumed fuels and subsequent emissions. Flaming emissions were also moderately sensitive to 10- and 100-h fuel loading. The most effective way to reduce uncertainty in flaming-phase emissions from wildfires is therefore to focus on data collection on the litter and 10- and 100-h fuel types.

In both models, smouldering phase emissions were moderately to highly sensitive to duff loading (Fig. 2*b*). The variability in duff loading was similar to or less than the variability in sound and rotten CWD variability (Table 3), therefore the variability alone cannot explain this sensitivity. Differences in model sensitivity to duff compared with CWD can be explained by the proportion of duff that was consumed and its contribution to smouldering phase emissions. On average, duff had a similar proportion consumed to sound and rotten CWD (Fig. 3*b*).

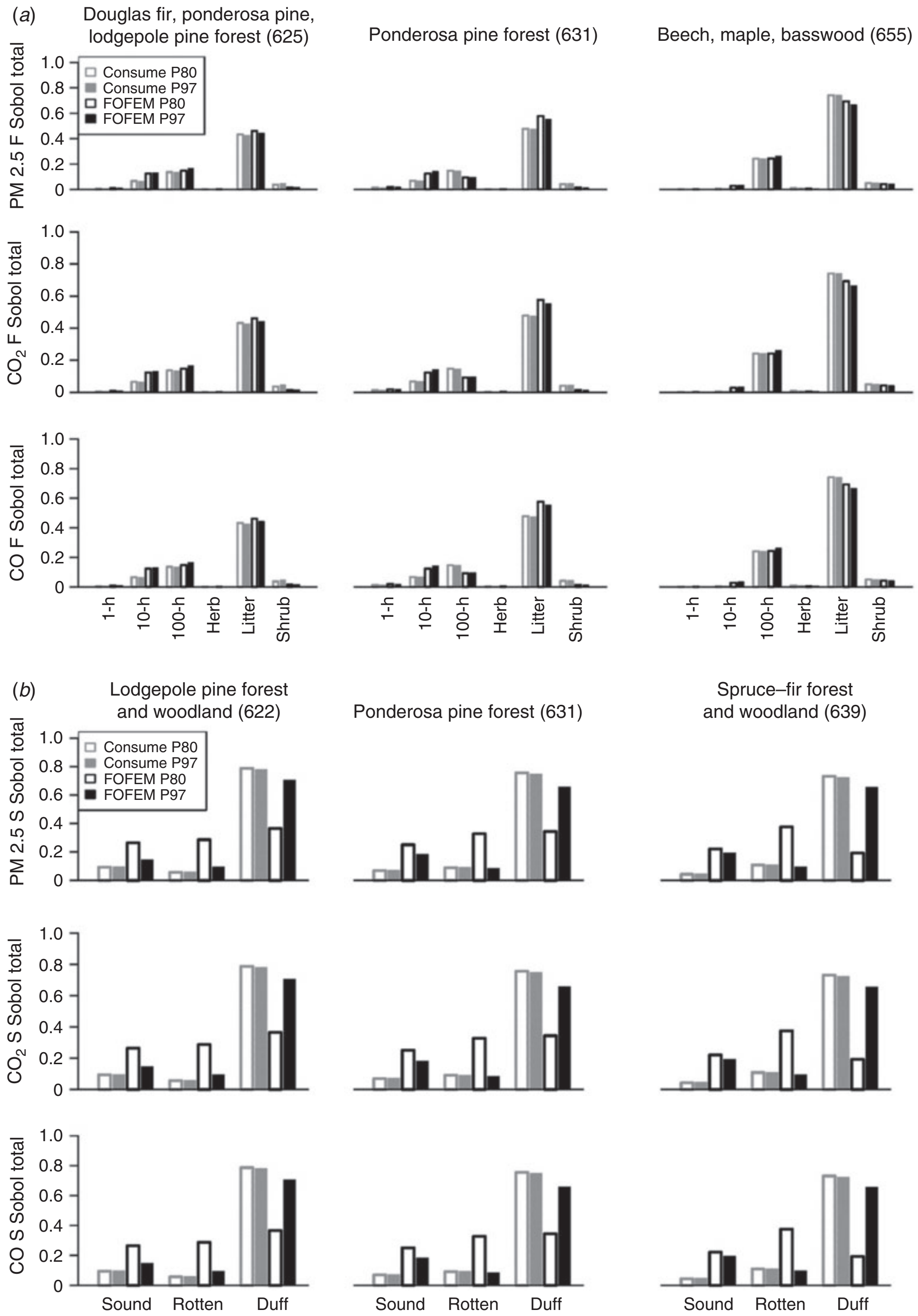


**Fig. 2.** Sobol total sensitivity index for fuels assumed to contribute to the (*a*) flaming phase of combustion (1-h, 10-h, 100-h, herb, litter and shrub) and for fuels assumed to contribute to the (*b*) smouldering phase of combustion (sound and rotten coarse woody debris and duff). Sensitivity of predicted emissions for CO, $CO_2$ and PM2.5 flaming (F) and smouldering (S) phases. Results are given for Consume (grey) and FOFEM (black) with 80th (P80; empty) and 97th (P97; filled) percentile environmental scenarios. FOFEM, First Order Fire Effects Model.

However, all of the duff consumption contributed to smouldering phase emissions, whereas sound and rotten CWD consumption may contribute to both flaming and smouldering phases (Lutes 2017). Smouldering emissions were also moderately sensitive to rotten CWD, particularly in the FOFEM predictions. These results imply that reducing uncertainty in duff-layer

**Table 4. Proportion of variability in fuel loading present in the variability in consumed fuels for the Consume model, when flaming fuels were sampled**

A value of 1 means that all of the variability in the fuel loading has propagated to variability in consumed fuels. A value of 0 indicates that none of the variability in the fuel loading has propagated to variability in consumed fuels. A value > 1 in total fuels indicates high proportion consumed or large correlations among the fuel components (corresponding to > 100%). EVG, existing vegetation group

| EVG | Environmental scenario | 1-h | 10-h | 100-h | Herb | Litter | Shrub | Total |
|---|---|---|---|---|---|---|---|---|
| Douglas fir, ponderosa pine, lodgepole pine forest (625) | 80 | 0.72 | 0.72 | 0.51 | 0.86 | 0.46 | 0.79 | 0.53 |
| | 97 | 0.72 | 0.72 | 0.51 | 0.86 | 0.46 | 0.99 | 0.53 |
| Ponderosa pine forest (631) | 80 | 0.72 | 0.72 | 0.51 | 0.86 | 0.46 | 0.9 | 0.52 |
| | 97 | 0.72 | 0.72 | 0.51 | 0.86 | 0.46 | 1.00 | 0.53 |
| Beech, maple, basswood (655) | 80 | 0.69 | 0.14 | 0.33 | 0.94 | 0.48 | 0.5 | 0.42 |
| | 97 | 0.69 | 0.14 | 0.33 | 0.94 | 0.48 | 0.5 | 0.42 |

**Table 5. Proportion of variability in fuel loading present in the variability in consumed fuels for the FOFEM model**

A value of 1 means that all of the variability in the fuel loading has propagated to variability in consumed fuels. A value of 0 indicates that none of the variability in the fuel loading has propagated to variability in consumed fuels. A value > 1 in total fuels indicates high proportion consumed or large correlations among the fuel components (corresponding to > 100%). EVG, existing vegetation group; FOFEM, First Order Fire Effects Model

| EVG | Environmental scenario | 1-h | 10-h | 100-h | Herb | Litter | Shrub | Total |
|---|---|---|---|---|---|---|---|---|
| Douglas fir, ponderosa pine, lodgepole pine forest (625) | 80 | 1.00 | 1.00 | 1.01 | 1.00 | 1.00 | 0.36 | 1.04 |
| | 97 | 1.00 | 1.00 | 1.00 | 1.00 | 1.00 | 0.36 | 1.01 |
| Ponderosa pine forest (631) | 80 | 1.00 | 1.00 | 1.00 | 1.00 | 1.00 | 0.36 | 1.23 |
| | 97 | 1.00 | 1.00 | 1.00 | 1.00 | 1.00 | 0.36 | 1.06 |
| Beech, maple, basswood (655) | 80 | 1.00 | 1.00 | 0.97 | 0.81 | 0.64 | 0.67 | 0.62 |
| | 97 | 1.00 | 1.00 | 0.98 | 0.81 | 0.64 | 0.70 | 0.57 |

loading, either by direct pre-fire measurement or by expanding the measurement of duff loadings across different vegetation types, is advisable. A secondary emphasis would be measurement of rotten CWD.

The prediction uncertainty in emissions illustrates only two key types of uncertainty: data inputs and model structure. How variability in the loading of different fuel components propagates to variability in consumed fuels (Eqn 3) depends on (1) correlations between loading components (e.g. a strong positive correlation increases propagation of variability) and (2) the proportion of consumed fuels predicted by the model. Both the variability in fuel loading and correlations among fuel components are characteristics of the fuel loading distributions in the NAWFD and represent data input uncertainty given our current state of knowledge for fuel loading. The proportion of consumed fuels is a consequence of model structure (e.g. empirical regression in Consume *v.* process-based in FOFEM) and represents the contribution of model structure to the propagation of data input uncertainty.

Consume and FOFEM have contrasting methods to predict fuel consumption and emissions. Consume's structure is relatively simple, using individual regression equations often with only pre-fire loading as an explanatory variable (e.g. Prichard *et al.* 2017). This empirical approach includes explanatory variables only if they are supported statistically and directly with data, rather than presumed theoretical relationships. These empirical relationships were estimated from prescribed burn studies, which were conducted under relatively narrow environmental conditions. Such lack of variability in environmental predictors makes it difficult to detect the effects of such variables on fuel consumption.

This outcome has the advantage of a relatively simple model structure, but a disadvantage that in the real world it is unlikely that the proportion consumed is constant for a given fuel loading; it likely does depend on other variables. Another disadvantage of strictly empirical models is that they have a relatively restricted domain of application, where extrapolations of the estimated relationship outside of the data or systems used for estimation is inappropriate.

In contrast, FOFEM also uses empirical models, some relatively simple and others less so, but integrates the process-based BURNUP model to predict fire intensity and fuel consumption (with BURNUP calibrated against empirical data; Albini *et al.* 1995; Albini and Reinhardt 1997). An advantage of process-based models is that, because they represent the mechanics of the underlying dynamics, they should be more robust than empirical models to applications in different systems and under different conditions (Hoffman *et al.* 2018). The structure of a process-based model reflects basic scientific knowledge of the system, although as a model it is still a simplification of that system, with associated uncertainties and potential sources of model inadequacies, which may be difficult to identify (Reynolds and Ford 1999). As complexity of a process-based model increases, it requires more precise and detailed model inputs, each with its own associated uncertainty (Hanhna 1988; Jansen 1998; Environmental Protection Agency 2009).

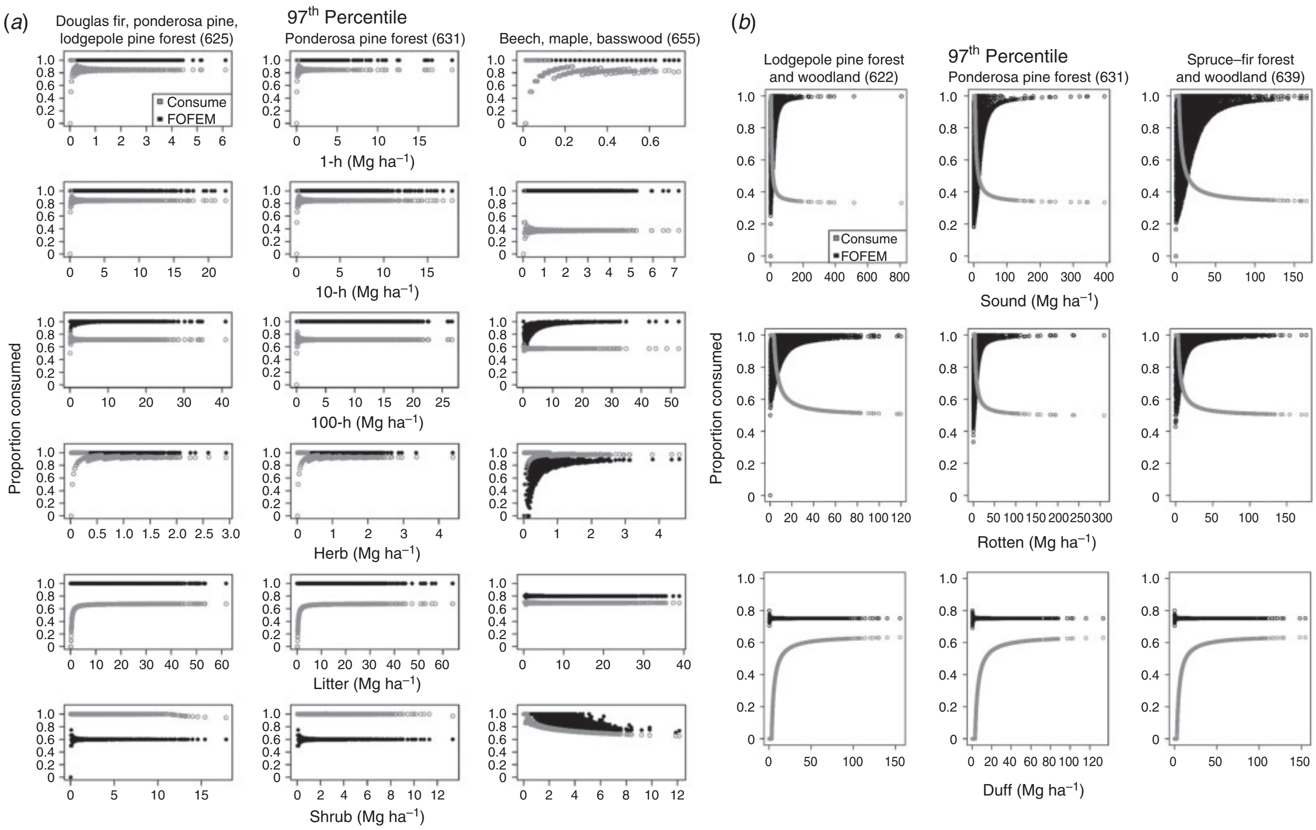


**Fig. 3.** Proportion consumed for (*a*) flaming fuel types and (*b*) smouldering fuel types against fuel loading for both models, under 97th percentile environmental conditions. Proportion consumed for 80th percentile weather conditions can be found in the Supplementary Material online. FOFEM, First Order Fire Effects Model.

The complexity of process-based models makes it more difficult to intuitively understand how different results are generated. The internal parameter values are often calibrated against data or some other criteria (e.g. Albini and Reinhardt 1997). For example, BURNUP was calibrated against burning rates in a controlled experiment and from a small set of controlled burns (prescribed fires and slash burning; Albini *et al.* 1995). Combinations of values for BURNUP parameters were found that best matched model predictions to observations for that set of controlled fires. Although good correspondence between model predictions and data lends confidence to the model, it does not assess whether the model structure itself is an adequate representation of system processes (Reynolds and Ford 1999). When a model is calibrated to a dataset, rather than representing actual relationships, the estimated parameter values may simply be accommodating the observed pattern. This situation is more likely as the number of parameters increases (i.e. the model is more complex). When the same model is calibrated to a different dataset, different parameter estimates may be generated (Kennedy and Ford 2011). It is possible that the model is showing a good fit to data with an inadequate model structure.

Rather than assess the relative adequacy of Consume and FOFEM, we focused on understanding differences in prediction uncertainty due to the underlying variability in the input data and how that interacts with the choice of emissions model. Model validation would require comparison of model predictions to observed fuel consumption and associated emissions. For example Prichard *et al.* (2014) found that either Consume or FOFEM better predicted observed fuel consumption, depending on fuel and vegetation types. Furthermore, uncertainty in the underlying structures and parameter estimates also contributes to uncertainty in model predictions, which we did not incorporate in this study. A general sensitivity analysis of emissions models would show how model structure and parameter uncertainty propagate to prediction uncertainty. This may involve calculating prediction intervals for fuel consumption from empirical regression equations (e.g. Prichard *et al.* 2017) or a sensitivity analysis of the parameters of a process-based model (e.g. Lutes 2013).

## *Conclusions and recommendations: reducing uncertainty*

A primary lesson from the NAWFD was that we do not have sufficient coverage of measured fuels in the USA to quantify, and thereby control for, spatial and temporal variability in fuel loading. Even with the extensive observations of fuel loading that were compiled in the NAWFD, many EVGs lacked enough observations to quantify distributions. Those EVGs that had sufficient observations were confined to distributions for a relatively coarse vegetation classification. Given this reality,

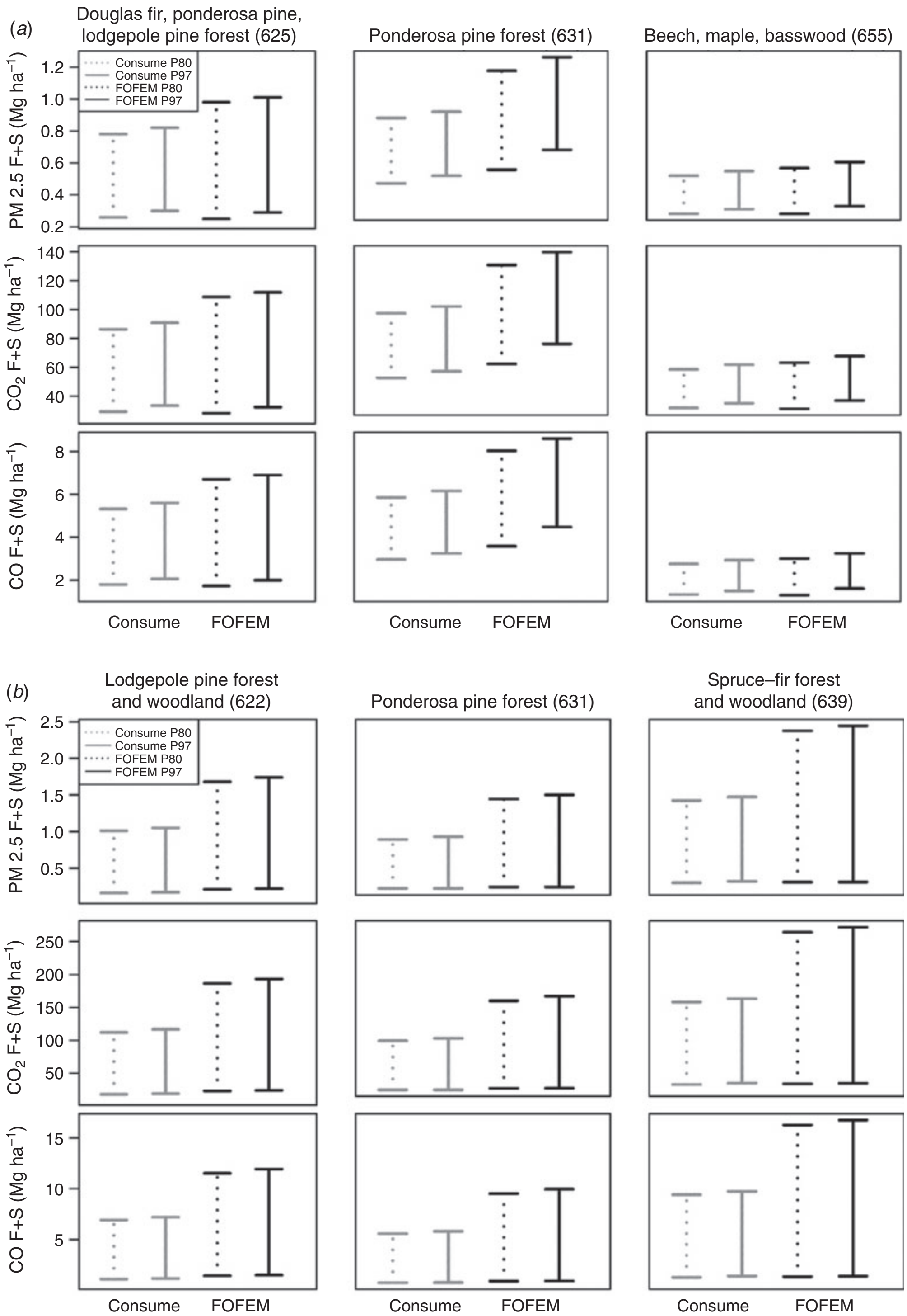


**Fig. 4.** Emissions 95% prediction intervals given variability in (*a*) flaming fuels (1-h, 10-h, 100-h, herb, litter, shrub) and (*b*) smouldering fuels (sound coarse woody debris (CWD), rotten CWD, duff). Grey is Consume, black is FOFEM. Dotted line is the 80th percentile environmental scenario, solid line is the 97th percentile environmental scenario. Emissions are total for the flaming and smouldering phases of combustion (F+S). Existing vegetation groups (EVGs) are Douglas fir, ponderosa pine, lodgepole pine (625), ponderosa pine forest (631), Beech, maple, basswood (655), lodgepole pine forest and woodland (622), and spruce-fir forest and woodland (639). FOFEM, First Order Fire Effects Model.

**Table 6. Proportion of variability in fuel loading present in the variability in consumed fuels for both models, when smouldering fuels were sampled**
A value of 1 means that all of the variability in the fuel loading has propagated to variability in consumed fuels. A value of 0 indicates that none of the variability in the fuel loading has propagated to variability in consumed fuels. A value > 1 in total fuels indicates high proportion consumed or large correlations among the fuel components (corresponding to > 100%). EVG, existing vegetation group; FOFEM, First Order Fire Effects Model; RCWD, rotten coarse woody debris; SCWD, sound coarse woody debris

| | | Consume | | | | FOFEM | | | |
|---|---|---|---|---|---|---|---|---|---|
| EVG | Environmental scenario | SCWD | RCWD | Duff | Total | SCWD | RCWD | Duff | Total |
| Lodgepole pine forest and woodland (622) | 80 | 0.11 | 0.26 | 0.40 | 0.21 | 0.93 | 0.86 | 0.50 | 0.86 |
| | 97 | 0.12 | 0.28 | 0.41 | 0.22 | 0.97 | 0.98 | 0.57 | 0.89 |
| Ponderosa pine forest (631) | 80 | 0.12 | 0.26 | 0.38 | 0.23 | 0.86 | 0.93 | 0.50 | 0.83 |
| | 97 | 0.13 | 0.27 | 0.40 | 0.24 | 0.93 | 0.99 | 0.57 | 0.88 |
| Spruce-fir forest and woodland (639) | 80 | 0.12 | 0.25 | 0.41 | 0.25 | 0.85 | 0.98 | 0.50 | 0.86 |
| | 97 | 0.13 | 0.26 | 0.41 | 0.26 | 0.95 | 1.00 | 0.57 | 0.88 |

associated uncertainty in emissions that are based on fuel loading distributions is quite high (Fig. 4). The variability quantified by the NAWFD, however, is not irreducible. Improved fuels inventories can reduce uncertainty in emissions estimates used for land management planning (Kasischke and Penner 2004).

This analysis indicates two ways by which uncertainty in predicted pollutant emissions due to variability in fuel loading inputs can be reduced. The first, and perhaps the most obvious, is to measure fuel loadings directly before a wildfire or prescribed fire (Larkin *et al.* 2009). This would control for the potential variability in fuel loading in a fire perimeter or planning area and is the best way to address local questions. It is not always possible to measure fuels, however, particularly before an unplanned fire. Furthermore, because fuels and environmental conditions vary geographically and over time, such measurements will be site-specific and applicable over a particular time frame. The second method to reduce uncertainty is to increase the measurements of fuel loading across vegetation types and within vegetation types that have little available data. With enough data from different site conditions and vegetation types, and a rigorous analysis of uncertainty (e.g. Prichard *et al.* 2019), emissions models can be applied more confidently in areas where fires have not occurred (but may be expected), albeit with less precision than on sites for which direct observations exist.

In the process of evaluating the NAWFD, Prichard *et al.* (2019) found biases in the vegetation types that had fuel measurements. The sparse coverage of existing measured fuels across vegetation types required a coarse aggregation into EVGs. A given EVG comprises multiple vegetation types and this coarser classification, therefore, has more sources of variability than would a finer classification. If sufficient measurements of fuel loading were available to quantify distributions for finer vegetation types, with a focus on those EVGs with the most variable fuel loading, then it may be possible to reduce the uncertainty associated with these sources of variability. Such reduction in variability of fuel loading input would propagate to narrower emissions prediction intervals when pre-fire fuel loadings cannot be measured directly. For some fire-prone fuel types, it may be desirable to develop this type of comprehensive sampling database, so predictions from sites commonly burned can be made with less uncertainty.

It is also possible that new directions of research, which investigate the spatial and temporal sources of variability in fuel loading, may mitigate the uncertainty we have documented. Increasing coverage of measured fuels would allow for distributions to be characterised for finer vegetation classes (as above) and could refine spatial and temporal scaling relationships for fuels (Keane *et al.* 2012). For example, incorporating management and disturbance history would further refine fuel loading estimates. This is especially important for smouldering fuels, which have much higher variability overall than flaming fuel components and thus wider prediction intervals for emissions.

The results of this uncertainty and sensitivity analysis indicate steps that can be taken to reduce uncertainty in emissions estimates.

1. Invest in additional biomass measurements across variable vegetation types, with a focus on those vegetation groups most common and typically fire-affected that are not well represented in the database. Contribute these measurements to the NAWFD. Within the more heterogeneous of these groups more sampling may be needed, especially in types with deep duff layers, which are important predictors of smouldering combustion.
2. For local fire and smoke management, dedicate resources to measuring litter biomass and smouldering fuels, including CWD and duff in areas expected to be affected by wildland fire emissions.
3. Perform full model assessments of Consume and FOFEM, including validation and sensitivity analysis, to characterise uncertainty in model structure.
4. Develop methods to integrate new information on variable fuel loadings into operational fuel classification maps and emissions models, rather than relying on generalised information and broad assumptions about fuel loadings. When that is not feasible, integrate an error metric into the model so the variability of fuels can be accounted for in an uncertainty assessment.

## Conflicts of interest

The authors declare no conflicts of interest.

## Acknowledgements

This research was completed with funding from the Joint Fire Science Program under Project JFSP 15-1-01-1 and National Fire Plan funding from the US Forest Service. Duncan Lutes provided helpful suggestions that greatly improved the manuscript. We thank Katalina Biondi, Heather St John and Marion LaRocque for their help in developing and testing scripts used in the analysis and Anne Andreu, Paige Eagle and Brian Drye for database development. The sampling method used here to conduct uncertainty analysis is available publicly for the USA, along with the source database (https://fuels.mtri.org). It is also intended that this database be updated as new data become available.

## References

Abatzoglou JT, Williams AP (2016) Impact of anthropogenic climate change on wildfire across western US forests. *Proceedings of the National Academy of Sciences of the United States of America* **113**, 11770–11775. doi:10.1073/PNAS.1607171113

Albini FA, Reinhardt ED (1995) Modeling ignition and burning rate of large woody natural fuels. *International Journal of Wildland Fire* **5**, 81–91. doi:10.1071/WF9950081

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

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

Beck MB (1987) Water quality modeling: a review of the analysis of uncertainty. *Water Resources Research* **23**, 1393–1442. doi:10.1029/WR023I008P01393

Bowman DMJS, Balch JK, Artaxo P, Bond WJ, Carlson JM, Cochrane MA, Antonio CMD, Defries RS, Doyle JC, Harrison SP, Johnston FH, Keeley JE, Krawchuk MA (2009) Fire in the Earth system. *Science* **324**, 481–484. doi:10.1126/SCIENCE.1163886

Cariboni J, Gatelli D, Liska R, Saltelli A (2007) The role of sensitivity analysis in ecological modelling. *Ecological Modelling* **203**, 167–182. doi:10.1016/J.ECOLMODEL.2005.10.045

Cascio WE (2018) Wildland fire smoke and human health. *The Science of the Total Environment* **624**, 586–595. doi:10.1016/J.SCITOTENV.2017.12.086

Collins B, Stephens S, Moghaddas JJ, Battles J (2010) Challenges and approaches in planning fuel treatments across fire-excluded forested landscapes. *Journal of Forestry* **108**, 24–31.

Drury SA, Larkin NS, Strand TT, Huang S, Strenfel SJ, Banwell EM, O'Brien TE, Raffuse SM (2014) Intercomparison of fire size, fuel loading, fuel consumption, and smoke emissions estimates on the 2006 Tripod fire, Washington, USA. *Fire Ecology* **10**, 56–83. doi:10.4996/FIREECOLOGY.1001056

Environmental Protection Agency (2009) Office of the Science Advisor: Guidance on the development, evaluation, and application of environmental models. EPA/100/K-09/003|March2009. Available at https://www.epa.gov/measurements-modeling/guidance-document-development-evaluation-and-application-environmental-models [Verified xxxx]

Fann N, Alman B, Broome RA, Morgan GG, Johnston FH, Pouliot G, Rappold AG (2018) The health impacts and economic value of wildland fire episodes in the U.S.: 2008–2012. *The Science of the Total Environment* **610–611**, 802–809. doi:10.1016/J.SCITOTENV.2017.08.024

Flannigan MD, Krawchuk MA, de Groot WJ, Wotton MB, Gowman LM (2009) Implications of changing climate for global wildland fire. *International Journal of Wildland Fire* **18**, 483–507. doi:10.1071/WF08187

Forkel M, Dorigo W, Lasslop G, Chuvieco E, Hantson S, Heil A, Teubner I, Thonicke K, Harrison SP (2019) Recent global and regional trends in burned area and their compensating environmental controls. *Environmental Research Communications* **1**, 051005. doi:10.1088/2515-7620/AB25D2

French NHF, Goovaerts P, Kasischke ES (2004) Uncertainty in estimating carbon emissions from boreal forest fires. *Journal of Geophysical Research, D, Atmospheres* **109**, D14S08. doi:10.1029/2003JD003635

Giglio L, Randerson JT, Van Der Werf GR (2013) Analysis of daily, monthly, and annual burned area using the fourth-generation global fire emissions database (GFED4). *Journal of Geophysical Research. Biogeosciences* **118**, 317–328. doi:10.1002/JGRG.20042

Hanhna SR (1988) Air quality model evaluation and uncertainty. *JAPCA* **38**, 406–412. doi:10.1080/08940630.1988.10466390

Hoffman C, Sieg C, Linn R, Mell W, Parsons R, Ziegler J, Hiers J (2018) Advancing the science of wildland fire dynamics using process-based models. *Fire* **1**, 32. doi:10.3390/FIRE1020032

Hough WA (1978) Estimating available fuel weight consumed by prescribed fires in the south. USDA Forest Service Research Paper SE-187, 12.

Iman R, Conover W (1982) A distribution-free approach to inducing rank correlation among input variables. *Communications in Statistics. Simulation and Computation* **11**, 311–334. doi:10.1080/03610918208812265

Jansen MJW (1998) Prediction error through modelling concepts and uncertainty from basic data. In 'Soil and water quality at different scales.' Developments in Plant and Soil Sciences, Vol. 80. (Eds PA Finke, J Bouma, MR Hoosbeek) pp. 247–253. (Springer: Dordrecht, The Netherlands)

Kalies EL, Yocom Kent LL (2016) Tamm Review: Are fuel treatments effective at achieving ecological and social objectives? A systematic review. *Forest Ecology and Management* **375**, 84–95. doi:10.1016/J.FORECO.2016.05.021

Kasischke ES, Penner JE (2004) Improving global estimates of atmospheric emissions from biomass burning. *Journal of Geophysical Research, D, Atmospheres* **109**, D14S01. doi:10.1029/2004JD004972

Keane RE (2015) 'Wildland fuel fundamentals and applications.' (Springer: New York)

Keane RE, Gray K, Bacciu V, Leirfallom S (2012) Spatial scaling of wildland fuels for six forest and rangeland ecosystems of the northern Rocky Mountains, USA. *Landscape Ecology* **27**, 1213–1234. doi:10.1007/S10980-012-9773-9

Keane RE, Herynk JM, Toney C, Urbanski SP, Lutes DC, Ottmar RD (2013) Evaluating the performance and mapping of three fuel classification systems using Forest Inventory and Analysis surface fuel measurements. *Forest Ecology and Management* **305**, 248–263. doi:10.1016/J.FORECO.2013.06.001

Kennedy MC, Ford ED (2011) Using multicriteria analysis of simulation models to understand complex biological systems. *Bioscience* **61**, 994–1004. doi:10.1525/BIO.2011.61.12.9

Larkin NK, O'Neill SM, Solomon R, Raffuse S, Strand T, Sullivan DC, Krull C, Rorig M, Peterson J, Ferguson SA (2009) The BlueSky smoke modeling framework. *International Journal of Wildland Fire* **18**, 906–920. doi:10.1071/WF07086

Littell JS, McKenzie D, Wan HY, Cushman SA (2018) Climate change and future wildfire in the western United States: an ecological approach to nonstationarity. *Earth's Future* **6**, 1097–1111. doi:10.1029/2018EF000878

Liu Y, Goodrick S, Heilman W (2014) Wildland fire emissions, carbon, and climate: wildfire–climate interactions. *Forest Ecology and Management* **317**, 80–96. doi:10.1016/J.FORECO.2013.02.020

Liu JC, Pereira G, Uhl SA, Bravo MA, Bell ML (2015) A systematic review of the physical health impacts from non-occupational exposure to wildfire smoke. *Environmental Research* **136**, 120–132. doi:10.1016/J.ENVRES.2014.10.015

Lutes DC (2013) Predicted down woody fuel consumption in the burnup model: sensitivity to four user inputs. USDA Forest Service, Rocky Mountain Research Station, Research Note RMRS-RN-51WWW. (Fort Collins, CO, USA)

Lutes DC (2017) 'FOFEM 6.4 user guide.' (USDA Forest Service, Fire and Aviation Management, Rocky Mountain Research Station, Fire Modeling Institute: Fort Collins, CO)

Lutes DC, Keane RE, Caratti JF (2009) A surface fuel classification for estimating fire effects. *International Journal of Wildland Fire*. doi:10.1071/WF08062

McIver J, Ottmar R (2007) Fuel mass and stand structure after post-fire logging of a severely burned ponderosa pine forest in northeastern Oregon. *Forest Ecology and Management* **238**, 268–279. doi:10.1016/J.FORECO.2006.10.021

McKenzie D, French NHF, Ottmar RD (2012) National database for calculating fuel available to wildfires. *Eos (Washington, D.C.)* **93**, 57–58. doi:10.1029/2012EO060002

O'Neill RV, Gardner RH (1979) Sources of uncertainty in ecological models. In 'Methodology in systems modelling and simulation' (Eds BP Zeigler, MS Elzas, GJ Klir, TI Oren) pp. 447–463. (North-Holland Publishing Company: Amsterdam)

Ottmar RD (2014) Wildland fire emissions, carbon, and climate: modeling fuel consumption. *Forest Ecology and Management* **317**, 41–50. doi:10.1016/J.FORECO.2013.06.010

Ottmar RD, Pritchard SJ, Vihnanek RE, Sandberg DV (2006) Modification and validation of fuel consumption models for shrub and forested lands in the Southwest, Pacific Northwest, Rockies, Midwest, Southeast and Alaska. Final Report to the Joint Fire Science Program. JFSP Project No. 98-1-9-06. USDA Forest Service, Pacific Northwest Research Station, Pacific Wildland Fire Sciences Laboratory, Fire and Environmental Research Applications (FERA). (Seattle, WA, USA)

Pereira JMC (2003) Remote sensing of burned areas in tropical savannas. *International Journal of Wildland Fire* **12**, 259–270. doi:10.1071/WF03028

Peterson J, Lahm P, Fitch M, George M, Haddow D, Melvin M, Hyde J, Eberhardt E (2018) NWCG smoke management guide for prescribed fire. National Wildfire Coordinating Group PMS 420-2, NFES 001279.

Prichard SJ, Karau E, Ottmar R, Kennedy M, Cronan J, Wright C, Keane RE (2014) Evaluation of the CONSUME and FOFEM fuel consumption models in pine and mixed hardwood forests of the eastern United States. *Canadian Journal of Forest Research* **44**, 784–795. doi:10.1139/CJFR-2013-0499

Prichard SJ, Kennedy MC, Wright CS, Cronan JB, Ottmar RD (2017) Predicting forest floor and woody fuel consumption from prescribed burns in southern and western pine ecosystems of the United States. *Forest Ecology and Management* **405**, 328–338. doi:10.1016/J.FORECO.2017.09.025

Prichard SJ, Kennedy MC, Andreu AG, Eagle PC, French NH, Billmire M (2019) Next-generation biomass mapping for regional emissions and carbon inventories: incorporating uncertainty in wildland fuel characterization. *Journal of Geophysical Research. Biogeosciences* **124**, 3699–3716. doi:10.1029/2019JG005083

Prichard SJ, O'Neill SM, Eagle P, Andreu AG, Drye B, Dubowy J, Urbanski S, Strand TM (2020) Wildland fire emission factors in North America: synthesis of existing data, measurement needs and management applications. *International Journal of Wildland Fire* **29**, 132–147. doi:10.1071/WF19066

Quinn-Davidson LN, Varner JM (2012) Impediments to prescribed fire across agency, landscape and manager: an example from northern California. *International Journal of Wildland Fire* **21**, 210–218. doi:10.1071/WF11017

Reid CE, Jerrett M, Balmes JR, Brauer M, Elliott CT, Johnston FH (2016) Critical review of health impacts of wildfire smoke exposure. *Environmental Health Perspectives* **124**, 1334–1343. doi:10.1289/EHP.1409277

Reinhardt E (2003) Using FOFEM 5.0 to estimate tree mortality, fuel consumption, smoke production and soil heating from wildland fire. In 'Proceedings of the Second International Wildland Fire Ecology and Fire Management Congress and Fifth Symposium on Fire and Forest Meteorology', 16–20 November 2003, Orlando, FL. American Meteorological Society, P5.2.

Reynolds JH, Ford ED (1999) Multi-criteria assessment of ecological process models. *Ecology* **80**, 538–553. doi:10.1890/0012-9658(1999)080[0538:MCAOEP]2.0.CO;2

Riaño D, Moreno Ruiz JA, Isidoro D, Ustin SL (2007) Global spatial patterns and temporal trends of burned area between 1981 and 2000 using NOAA-NASA Pathfinder. *Global Change Biology* **13**, 40–50. doi:10.1111/J.1365-2486.2006.01268.X

Rollins MG (2009) LANDFIRE: a nationally consistent vegetation, wildland fire, and fuel assessment. *International Journal of Wildland Fire* **18**, 235–249. doi:10.1071/WF08088

Ryan KC, Knapp EE, Varner JM (2013) Prescribed fire in North American forests and woodlands: history, current practice, and challenges. *Frontiers in Ecology and the Environment* **11**, e15–e24. doi:10.1890/120329

Saltelli A, Annoni P, Azzini I, Campolongo F, Ratto M, Tarantola S (2010) Variance based sensitivity analysis of model output: design and estimator for the total sensitivity index. *Computer Physics Communications* **181**, 259–270. doi:10.1016/J.CPC.2009.09.018

Shi Y, Matsunaga T, Saito M, Yamaguchi Y, Chen X (2015) Comparison of global inventories of $CO_2$ emissions from biomass burning during 2002–2011 derived from multiple satellite products. *Environmental Pollution* **206**, 479–487. doi:10.1016/J.ENVPOL.2015.08.009

Sobol' I (2001) Global sensitivity indices for nonlinear mathematical models and their Monte Carlo estimates. *Mathematics and Computers in Simulation* **55**, 271–280. doi:10.1016/S0378-4754(00)00270-6

Turley MC, Ford ED (2009) Definition and calculation of uncertainty in ecological process models. *Ecological Modelling* **220**, 1968–1983. doi:10.1016/J.ECOLMODEL.2009.04.046

Urbanski S (2014) Wildland fire emissions, carbon, and climate: emission factors. *Forest Ecology and Management* **317**, 51–60. doi:10.1016/J.FORECO.2013.05.045

Urbanski SP, Hao WM, Nordgren B (2011) The wildland fire emission inventory: western United States emission estimates and an evaluation of uncertainty. *Atmospheric Chemistry and Physics* **11**, 12973–13000. doi:10.5194/ACP-11-12973-2011

Wright CS (2013*a*) Models for predicting fuel consumption in sagebrush-dominated ecosystems. *Rangeland Ecology and Management* **66**, 254–266. doi:10.2111/REM-D-12-00027.1

Wright CS (2013*b*) Fuel consumption models for pine flatwoods fuel types in southeastern United States. *Southern Journal of Applied Forestry* **37**, 148–159. doi:10.5849/SJAF.12-006