Quantifying uncertainty for predictions of wildfire emissions: Sensitivity and Uncertainty analysis

Sensitivity of estimated emissions to fuel loading uncertainty in major vegetation types of the United States

Maureen C. Kennedy (corresponding author)

University of Washington, Tacoma. School of Interdisciplinary Arts and Sciences, Division of Sciences and Mathematics. 1900 Commerce St., Tacoma, WA, 98402.

mkenn@uw.edu

Authors:

Abstract:

Keywords: uncertainty analysis; sensitivity analysis; Consume; FOFEM; prediction interval;

Introduction

Air quality impacts from wildfire smoke emissions are associated with increased emergency room admissions (ref) and cardio-pulmonary symptoms (ref), particularly for vulnerable populations (ref). Wildfire area burned in the Western United States has increased in the last few decades (ref) and is expected to continue to increase (ref), with associated increases in pollution emissions (Spracklen et al., 2009). Prescribed fire is a forest management tool used to reduce fuel loads with multiple objectives including the reduction of subsequent fire hazard. There are air quality concerns and regulations that can act as a barrier to implementing prescribed fire as a management tool (Quinn-Davidson and Varner, 2012) (ref). To plan for future wildfire emissions and forest management using prescribed fire it is imperative to credibly represent possible emissions. This includes an estimation of the uncertainty associated with such predictions.

There are multiple sources that contribute to the total uncertainty in model prediction, and these can be classified broadly into four groups: model structure uncertainty, parameter estimation uncertainty, data input uncertainty, and natural variability/stochasticity (Beck, 1987; O’neill and Gardner, 1979; Turley and Ford, 2009). Uncertainty and sensitivity analysis is a class of model assessment that evaluates these sources of uncertainty and quantifies how they propagate to uncertainty in model predictions. Usually sensitivity analysis is concerned with assessing the sensitivity of target model outputs (such as the prediction of particulate emissions) to variability in parameter values (Saltelli probably) or data inputs. The parameter values are then ranked by the relative sensitivity of model outputs. Uncertainty analysis is a related method that quantifies the uncertainty in model predictions given underlying uncertainty in data inputs and parameter values (ref).

The US Forest Service has two primary computing tools for predicting fuel consumption and associated emissions that may result from wildfire and prescribed fire. The Consume model (ref) and the First Order Fire Effects Model (FOFEM; ref) have been used for planning (ref?), (uses for Consume and FOFEM list and refs).

There are two major inputs required to predict emissions of important pollutants from wildfire: the loading (Mg ha-1) of important fuel types (list? Table maybe) and the environmental conditions for burning (list? Table maybe). Both of these may be sources of uncertainty for emissions predictions. It is rare to measure fuel loadings directly before a wildfire, and often studies of emissions rely on coarse maps (ref examples) that classify fuel types into fuel beds (such as the Fuels Characterization and Classification system; FCCS) or fuel loading models (FLMs) that are provided by the Landfire project (Rollins, 2009). Such maps give point values of fuel loading that, like most point estimates, are most likely not correct in a particular time or place (Keane et al., 2013). They also provide false precision for model estimates by returning point predictions for emissions, masking uncertainty in emissions due to uncertainty in fuel loading values.

Prichard et al. (in review at least we hope!) recently compiled a database of fuel loading aggregated by major Existing Vegetation Type Groups (EVG’s) classified by the Landfire project. For each fuel loading type with sufficient coverage they estimated empirical loading distributions using either the log-normal or gamma distributions. These empirical distributions provide an estimate of the variability and uncertainty in fuel loading amount for a given EVG and provide a resource to evaluate sensitivity and quantify uncertainty in prediction of pollution emissions from wildfire.

Recently the uncertainty in estimates of fuel consumption in Consume and FOFEM due to uncertainty in empirical coefficient estimates (a form of parameter uncertainty) has been quantified (Prichard et al., 2017, 2014). Here we focus on the contribution of data input uncertainty (fuel loading) to the sensitivity and uncertainty in wildfire emissions predictions using methods of global sensitivity analysis (Saltelli ref). Our overarching goal is to provide better information to inform wildfire management planning and to direct resources to the empirical efforts that will best help to reduce uncertainty in these predictions. To that end our specific objectives are to:

1. Identify the fuel loading types that contribute most to the sensitivity of the prediction of emissions in both the flaming and smoldering phases of combustion.
2. Assess whether sensitivity to fuel loading changes with environmental inputs.
3. Quantify the uncertainty of the prediction of emissions in both the flaming and smoldering phases of combustion given the variability in fuel loading quantified by Prichard et al. (status).

**Methods**

*Consume and FOFEM descriptions (susan?)*

*Test Case EVGs (from Database paper) and variable groupings; baseline fuelbeds*

We follow the example of Prichard et al. (status) and choose 6 candidate EVGs for our analysis. These represent major vegetation groups in the continental US. Of those groups, only \_\_\_ had sufficient coverage to estimate correlation matrices for the target fuel loading types. Those groups are evaluated here.

For sensitivity and uncertainty analysis we group fuel types into those understood to be important for the flaming stage of combustion (100-hr, 10-hr, 1-hr, herb, litter, shrub) and those understood to be important for the smoldering phase of combustion (sound CWD, rotten CWD, and duff). We reduced all possible loadings to these combinations to facilitate our ability to calculate correlation matrices for sampling (see below), increasing the chance we have complete cases in order to estimate the correlation matrix.

In order to use the Consume and FOFEM models to estimate emissions we must provide loadings for all required fuel types, not just those that are sampled. We followed Prichard et al. (status) who selected a representative FCCS fuelbed for each EVG to provide baseline value for all fuel loading types (Table). The values for those fuel loading types not sampled will remain constant at this baseline value for each EVG.

*Target outputs, and environmental variable settings.*

We assess the sensitivity with respect to three major emission types: CO, CO2, and PM2.5. (justification).

Environmental conditions for each EVG are specified at 97th and 80th percentile conditions (Table). Justification for conditions.

*Quantifying variability in fuel loading*

Prichard et al. (status) used a hurdle estimation procedure because of the large proportion of zeroes for some of the fuel loading types. Qualitatively, the hurdle to be crossed is having a non-zero fuel loading, and once that hurdle is crossed (x>0) a continuous distribution is estimated for the data. The density function for the jth fuel type in the kth EVT group (fkj(x)) can be written as (Lachenbruch 2002):

fkj(x,d)= πkj1-d((1-πkj)hkj(x))d, (1)

where h(x) is the estimated continuous distribution function (in this case, gamma or lognormal) for x>0, d = 1 if x non-zero, 0 if x 0, and π is the probability of observing a zero.

For the continuous portion of each fuel type in each EVT group they chose either a lognormal or a gamma distribution. The lognormal probability distribution function, with parameters μ, σ, is written as:

, (2)

where σx is the standard deviation of ln(x) and μ is the mean of ln(x).

The gamma probability distribution function, with parameters α, β, is written as:

. (3)

For our sensitivity and uncertainty analysis we sample from the empirical hurdle distributions estimated by Prichard et al. (status; Table for distribution estimates) using a 2-part procedure. Let *N* be the total number of loadings that are sampled. First we take a random draw from a binomial distribution where the parameter *p* is the estimated proportion of zero-valued entries for the given fuel type and EVG. Let *n* be the number of randomly drawn zero entries. We then sample *N-n = m* random draws from the estimated continuous portion of the distribution. All random samples are drawn using the R Statistical Package (R ref). This method provides samples from the independent marginal distributions of each fuel loading type. We also want to preserve possible correlation structures among fuel loading types, and we adapt the matrix-based methodology given by (Iman and Conover, 1982) to mimic the empirical rank correlation structure.

Let *K* be the number of fuel types that are targeted for the analysis (e.g., *K* = 6 for flaming fuel types). First *N* independent samples for each fuel type are generated from the best fitting marginal empirical distribution from the Prichard et al. fuels database for each target EVT, to create a matrix X (NxK). We then estimate Spearman’s rank correlation structure on the group of fuel types for the test case EVT groups, using only complete cases to estimate the correlation matrix (only cases for which all variables of interest are entered). We use the matrix method of (Iman and Conover, 1982) to approximate a given rank correlation structure for sampled input data, resulting in an NxK sampled input matrix X\* with correlation structure similar to the empirical correlation structure (see supplementary methods).

Global sensitivity Analysis (SA)

The goal of SA is to identify the fuel inputs with the strongest impact on emissions estimates. We will use both Sobol variance partitioning (vp) and partial rank correlation coefficients (prcc).

For the Sobol variance partitioning procedure we divide the NxK matrix X\* into two new (N/2)xK matrices, X1 and X2, where X1 is the first N/2 rows in X\* and X2 is the last N/2 rows in X\*. We then use the sobolEff function in the R sensitivity package (Pujol et al., 2017), where the function rearranges the X1 and X2 to create a new data input matrix. For example, for N=1000, the final data input X has 3500 rows. Note that this exchanges the columns in X1 and X2, and the rank correlation structure of the final data input matrix has a poorer approximation of the original correlation matrix (C; Supplementary; might want to look into this, might have dampened correlations relative to empirical).

Variance partitioning may not provide valid partitions in the case of correlated inputs (ref, one of the Saltelli books). We complement the variance partitioning results with the partial rank correlation coefficient (prcc; ref), which provides a non-parametric estimate of the correlation between each input and each output, accounting for any relationships among the inputs and between the remaining inputs and the output. As with standard correlations, the prcc takes values between -1 and 1. We will rank the inputs by their importance in variance partitioning, and by those with the greatest magnitude prcc. We will apply a bootstrap procedure for both indices to provide bootstrap standard errors and confidence intervals for the index value for each model input. Any inconsistent rankings between the two procedures will be evaluated further. The prcc values are obtained using the pcc function in the R sensitivity package (Pujol et al., 2017).

We also compare the rankings of both procedures to the rankings obtained from uncorrelated sampling from the marginal distributions across fuel types to assess the necessity to incorporate correlation structures in sensitivity and uncertainty analysis.

Sensitivity to environmental inputs

For each random sample of fuel loading values we apply a factorial design of environmental inputs, approximating extreme hazardous environmental conditions (97th percentile?) and moderate environmental conditions (80th percentile?). These conditions may differ by EVG, and are given in Table \_.

Quantifying uncertainty in emissions estimates

For the sampled matrix X\* we use the baseline fuelbed to fill in fuel types required for each model (see supplementary) and create an input file suitable for each model. We then use the model to estimate fuel consumption and emissions for each row in our input file, for the given environmental conditions. From the resulting model output file we characterize the distribution of predicted emissions (using boxplots and 95% intervals). This provides a link between the uncertainty in fuel loading as represented by the database, and the uncertainty in emission predictions. These intervals are created for both sets of environmental conditions.

Results

Correlation structures

Sensitivity indices

95% prediction intervals for each output based on global sampling

Discussion

Point estimates and predictions are insufficient

Much uncertainty in fuel loading data gives uncertainty in emissions predictions

Emissions are sensitive to all fuel loading categories when considered individually, but when taken as a whole the most sensitive fuel inputs are \_\_\_\_ for flaming and \_\_\_\_ for smoldering.

Sensitivities are themselves sensitive to environmental conditions (or are?)

Require better data to more precisely predict emissions. So many holes! Particularly to estimate correlation matrices

If OAT nearly all correlations are near 1—want to consider the system of fuels, not just one at a time.

**Supplementary Methods**

We adapt the method of (Iman and Conover, 1982) by first estimating Spearman’s rank correlation structure on the group of fuel types for the test case EVT groups, using only complete cases to estimate the correlation matrix (only cases for which all variables of interest are entered). Let C be the empirical correlation matrix (KxK). P’ is the Cholesky factorization of C (generated by the R chol function), and P is the transpose of the resulting matrix.

Define the scores a(i) (i=1,…,N):

Where φ-1 is the inverse of the cumulative distribution function for the standard normal distribution. Then we create a new NxK matrix R, where each column is an independent random sample (without replacement) from the vector of scores A (comprised of a(i) above). We then generate the matrix R\* as RP’. The matrix R\* will have a rank correlation structure similar to C.

To reduce the variability in the correlation in the sampled data input matrix, a new matrix correlation matrix (T) is generated as the Spearman rank correlation matrix for the matrix R\*. We then calculate Q’ as the Cholesky factorization of T, with Q the transpose of Q’. We solve for the matrix S = PQ-1, and R\*b = RS’. We then rearrange each column in the sampled data input matrix X to match the rankings in the matrix R\*b. For example, if the first row in R\*b is the 5th ordered statistic, then we place the 5th ordered statistic for that column in X in the first row (call the resulting matrix X\*). This preserves the overall marginal distribution for each column X\*, while approximating the rank correlation structure across each row in X\*.