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Identifying the most influential parameters in experimental grass fire spread modeling using global sensitivity analysis

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Abstract

Coupled atmosphere/fire models are recognized as an efficient and representative way to simulate wildland fire behavior at geographical-to-meteorological scales by representing the two-way interactions between the fire front propagation and the surrounding atmosphere. These coupled models rely on a rate-of-spread (ROS) parameterization to represent the fire front propagation speed as a parametric function of environmental factors characterizing biomass fuel properties and moisture content, near-surface wind conditions and terrain slope. In actual wildland fires, these input parameters are only partially known and induce significant uncertainties in the coupled model predictions. To estimate the envelope of plausible wildland fire behavior, we aim at designing a perturbed-physics ensemble prediction capability based on a coupled atmosphere/fire model. To make the approach feasible, it is essential to identify the relevant subset of parameters to perturb to generate an ensemble of fire front positions and shapes. In the present study, we carry out a global sensitivity analysis based on Sobol' indices to rank the environmental factors by order of influence on the Balbi's ROS parameterization applied to typical conditions for grass fire experiments. Results show, for the given experimental conditions, the predominance of the near-surface wind speed on the ROS variability, followed by the leaf area index LAI, the ignition temperature T_i, the dead fuel moisture content M_d, the dead fuel particle mass density ρ_d, and the fuel layer height e. Results also show that the sensitivity of each fuel parameter to the ROS is not constant with respect to the near-surface wind speed, and that the most influential input parameters differ between the head and the back of a fire. This indicates the importance of exploring the spatial and temporal dependencies of coupled model sensitivities in future work. The subset of input parameters already identified as influential allows to reduce the dimension of the uncertain space over which to analyze the coupled model response, and thereby the perturbed-physics ensemble size. This is a key aspect to extend the global sensitivity analysis to the coupled model framework. While the present sensitivity analysis is limited to experimental grass fire conditions, this approach could be easily extended to more wildland fire configurations - to analyze to what extend the sensitivity analysis results obtained here are applicable to different biomass fuels.

1. Introduction

Coupled atmosphere/fire models (Kochanski *et al.* 2013; Filippi *et al.* 2018; Costes *et al.* 2021) provide an efficient but representative way to simulate wildland fire behavior at landscape-to-meteorological scales. They predict the propagation of the fire front at the land surface, the dynamics of the fire plume, and their mutual interactions. These two-way interactions can modify the near-surface wind and enhance the fire front propagation during a wildland fire. The fire model requires from the atmospheric model the near-surface wind at a given height to evaluate the rate of spread (ROS) and propagate the fire front. It also provides the surface heat fluxes as surface boundary conditions to the atmospheric model. Both ROS (Rothermel 1972; Balbi *et al.* 2009) and surface heat fluxes are evaluated through parameterizations, which require as inputs a large number of environmental factors related to biomass fuel, near-surface wind and terrain slope. These input parameters are partially known (Jimenez *et al.* 2008) and thereby introduce uncertainties in the coupled simulations. They also have their own intrinsic variability. For these reasons, it is necessary to adopt a stochastic viewpoint, i.e., to run ensembles of the coupled atmosphere/fire model to represent the range of possible wildland fire behavior over a given time window (Costes *et al.* 2021).

To limit the computational cost of ensemble simulations while obtaining a physically and spatially-consistent ensemble, an appropriate experimental design is essential. The main issue addressed in this work is to identify a subset of input parameters that contributes most to the ROS variability along the fire front, and thus on the fire front propagation through variance-based global sensitivity analysis (Wilks 2011). The influential input parameters will be good candidates to perturb to build a perturbed-physics ensemble that is representative of fire front uncertainties in coupled atmosphere/fire modeling.

2. Global Sensitivity Analysis Method

2.1. Principles

The objective of sensitivity analysis is to quantify how uncertainties in each input parameter influence the output variability in a given model. This is useful to spot the most influential parameters on a given model response (factor prioritization), and to constrain irrelevant parameters to an arbitrary value (factor fixing) (Wilks 2011). There are two main types of sensitivity analysis methods. On the one hand, local methods are centered around one point in the parameter space, and, for each parameter, the impact of small parameter perturbations on the model output is calculated. They have some limitations if the model response is subject to nonlinearity since the local output variability may not be representative of the model response for all possible values of the input parameters. On the other hand, in the global methods, the entire parameter space is considered and the model response is analyzed in a multi-query framework, meaning that multiple model evaluations of simultaneously-modified input parameters are performed and that the induced model variability provides a measure of the parameter influence on the model output. Global methods are known to be very efficient, even for a nonlinear and non-monotonic model, where interactions between input parameters can occur. Still, their results largely depend on the parameter space boundaries and sampling.

2.2. Sobol' Sensitivity Indices

In the present study, we consider a global sensitivity analysis method based on variance decomposition (the model output variance is used as the measure of the input parameter influence on the overall model output variability) to estimate Sobol' sensitivity indices (Sobol 1990; Saltelli *et al.* 2008).

The model output Y is a function of d independent and uncertain input parameters, i.e., $Y = \mathcal{M}(X_1, \dots, X_d)$, where X_i is the ith parameter that is considered as a random variable, $\boldsymbol{X} = (X_1, \dots, X_d)$ is a random vector of dimension d, and $\mathcal{M}$ is the model operator. By using Hoeffding's decomposition theorem, the output variance $V = V(Y)$ can be written as

$$\mathrm{V} = \sum_{i=1}^{d} V_i + \sum_{1 \le i < j \le d} V_{ij} + \cdots + \mathrm{V}_{1\ldots\mathrm{d}},$$

where V_i is the output variance only due to parameter i, V_{ij} is the output variance due to the pair of parameters i and j, and $V_{1\ldots d}$ is the output variance due to the d parameters. Using these notations, Sobol' first-order index for the ith parameter X_i (Sobol 1990) is defined as

$$S_i = \frac{V_i}{V}.$$

S_i varies between 0 and 1, and represents the proportion of the model output variance due to the ith parameter (if S_i = 1, this means that 100% of the model output variance is explained by the ith parameter alone). By analogy, higher-order indices represent the proportion of the model output variance due to a set of parameters. The full contribution of the ith parameter (including interaction effects with other parameters) can be estimated using total-order indices S_i^T (Saltelli *et al.* 2008):

$$S_i^T = S_i + \sum_{j>i}^{d} S_{ij} + \cdots + S_{1,\ldots,d}.$$

The first-order index S_i represents the main effect of the *i*th parameter X_i that is used in factor privatization, and the total-order index S_i^T represents the total effect of the parameter that is used in factor fixing. The difference between the two indices represents to which extent the parameter effects on the model response comes from an interaction with the other parameters (if the total-order index for a given parameter is equal to its first-order index, this implies that there are no interaction effects for this parameter).

3. Sensitivity Analysis Application to Rate-Of-Spread (ROS) Parameterization

The model due to Rothermel (1972) is the most well-known ROS parameterization. Its formulation relies on the energy conservation principle and provides a ROS value only at the head of the fire front (i.e., in the upwind direction). In practice, Rothermel's formulation is combined with geometrical relationships to evaluate the ROS all along the fire front. This is the main difference with Balbi's parameterization (Balbi *et al.* 2009) that directly provides a ROS value that varies all along the fire front, even if the fuel is homogeneous. Balbi's formulation is based on mass, momentum and energy conservation, but still provides an analytical formulation for the ROS through flame geometry simplifications.

In this study, we consider Balbi's ROS parameterization adapted for landscape-scale wildland fires (Santoni *et al.* 2011) and already implemented in the Meso-NH/BLAZE coupled model. It was, for instance, used for the coupled model evaluation against the FireFlux I grass experimental data (Costes *et al.* 2021). The change made by Santoni *et al.* (2011) compared to Balbi *et al.* (2009) is the consideration of the different properties of live and dead fuels, and their impacts on the ROS. Following previous work by Costes *et al.* (2021), we consider here the conditions of a grass fire experiment, without slope, to carry out the sensitivity analysis. The slope parameter is therefore not among the perturbed input parameters.

3.1. Sobol'-Saltelli Estimation Approach and Experimental Design

We adopt the well-known Saltelli's approach (Saltelli *et al.* 2008) to estimate first- and total-order Sobol' indices (altogether $2 \times d$ indices, where d is the number of uncertain input parameters). This approach corresponds to a Monte Carlo estimation of the Sobol' indices at a total cost of $N \times (d + 2)$ ROS evaluations (where N is the ensemble size), and thereby provides a confidence interval for the resulting Sobol' indices estimates.

In this study, the uncertain space is made by all the input parameters of Balbi's ROS parameterization (fifteen parameters including the near-surface wind speed U_0, Table 1). This space is sampled by N points using Sobol' low-discrepancy sequence. This is a quasi-random Monte Carlo method, where the generated sequence has many interesting properties: *i)* the sequence has a low discrepancy (i.e., there is a more homogeneous coverage of the parameter space than in a classical Monte Carlo method for a limited number of samples N), and *ii)* the sequence is coherent (the N first points of a sequence with $(N + 1)$ points are the same as for a sequence with N points, implying that, if more samples must be generated, it is not necessary to recompute the previous points and that a large model dataset can be generated in an incremental way). It is worth noting that we consider here a large number of samples N to guarantee convergence of the Sobol' indices ($N = 20{,}000$). This is feasible here since the ROS parameterization can be evaluated at a low cost (the sampling strategy will have to be adapted when switching to a coupled atmosphere/fire model, which is very demanding in terms of computing resources). Table 1 provides a detailed description of the fifteen input parameters. Without further information, they are perturbed according to a uniform statistical distribution, which is characterized by a variation interval. The center of this interval corresponds to a so-called standard value, which corresponds to a tall grass fuel typical of the FireFlux I experiment that was simulated in Costes *et al.* (2021) using the Meso-NH/BLAZE coupled model configured with the Balbi's ROS parameterization. We consider here a large variation interval to study how the ROS changes for a wide set of environmental conditions, and to identify which are the most influential input parameters that could then be used to generate ensemble coupled model simulations and study the coupled model response in a variety of situations.

3.2. Results

3.2.1. Predominant wind factor

Figure 1 shows the first- and total-order sensitivity indices for all parameters presented in Table 1 ($d = 15$). For example, the first-order index for the dead fuel particle density ρ_d is equal to 0.05 (circle symbol), and the associated total-order index is equal to 0.06 (square gray symbol). This means that ρ_d is responsible for 6% of the ROS variability within the ensemble (5% without accounting for the interaction with the other parameters).

Table 1- Input parameters (Balbi's ROS parameterization) perturbed in the sensitivity analysis

Name	Symbol	Unit	Standard value	Lower bound	Upper bound	Coefficient of variation
Fuel calorific capacity	c_p	J kg^{-1} K^{-1}	1,912	1,720.8	2,103.2	6%
Fuel layer height	e	m	1.5	1.0	2.0	19%
Leaf area index	LAI	—	4	2	6	29%
Dead fuel moisture content	M_d	%	10	5	15	29%
Living fuel moisture content	M_l	%	80	60	100	14%
Dead fuel particle surface-to-volume ratio	s_d	m^{-1}	5,000	4,250	5,750	9%
Living fuel particle surface-to-volume ratio	s_l	m^{-1}	5,000	4,250	5,750	9%
Ignition temperature	T_i	K	590	490	690	10%
Near-surface wind speed	U_0	m s^{-1}	4	0	8	58%
Combustion enthalpy	ΔH	MJ kg^{-1}	15.43	14.66	16.20	3%
Air density	ρ_a	kg m^{-3}	1.2	1.0	1.4	10%
Dead fuel particle mass density	ρ_d	kg m^{-3}	400	300	500	14%
Living fuel particle mass density	ρ_l	kg m^{-3}	400	300	500	14%
Dead fuel surface loading	σ_d	kg m^{-2}	1	0.8	1.2	12%
Living fuel surface loading	σ_l	kg m^{-2}	0.1	0.05	0.15	29%

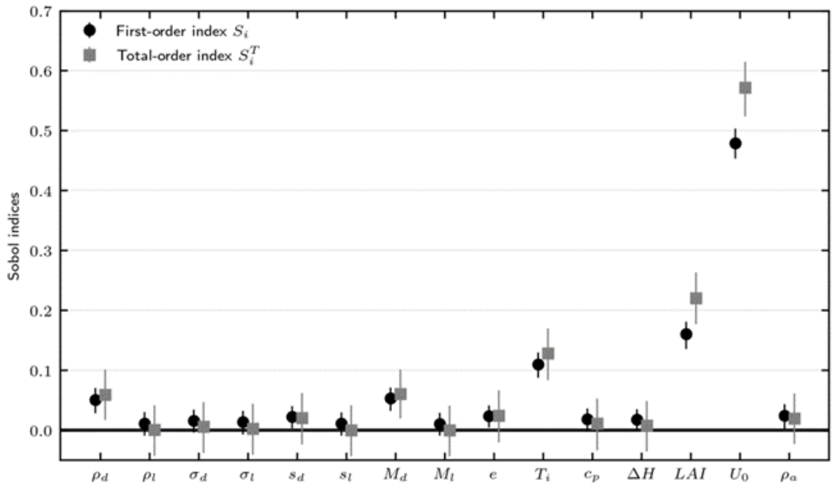

Figure 1- Sobol' indices quantifying the sensitivity between the 15 perturbed parameters and the ROS as evaluated by Balbi's parameterization at the fire front head. Circles represent first-order indices. Squares represent total-order indices. Vertical bars represent estimation uncertainties.

From Figure 1, the most influential parameters on the Balbi's ROS parameterization can be identified. The near-surface wind speed U_0 is the predominant factor by explaining by itself 48% of the ROS variability (57% in total). The difference between the first- and total-order indices is important for U_0, implying that there are important interaction effects between the wind factor and the other parameters. Other influential parameters are by order of importance the leaf area index LAI, the ignition temperature T_i, the dead fuel moisture content M_d, and the dead fuel particle mass density ρ_d for which the first-order Sobol' index is equal to 16%, 11%, 5% and 5%, respectively.

3.2.2. Sensitivity analysis by near-surface wind speed level

Previous results correspond to the ROS at the head of the fire front. We now apply the same sensitivity analysis method when the near-surface wind speed U_0 is equal to 0 m s^{-1}, in order to represent the situation of a back fire (fourteen parameters are perturbed). The most influential parameters are by order of importance the fuel layer height e, the ignition temperature T_i, the combustion enthalpy ΔH, the dead fuel moisture content M_d and the dead fuel surface loading σ_d for which the first-order Sobol' index is equal to 38%, 21%, 9%, 8% and 8%, respectively. This shows that T_i and M_d are influential parameters at the head and at the back of a fire.

This results also indicates that the sensitivity of the ROS to the different fuel parameters is variable according to the value of the near-surface wind speed U_0. This is consistent with the difference previously-observed between the first- and total-order Sobol' indices for the near-surface wind speed U_0 indicating significant interaction effects. Since the wind velocity seen by the fire front changes all along the fire front (the wind speed used in the ROS parameterization corresponds to the normal component of the wind velocity to the fire front), the order of importance of the input parameters may change along the fire front. To further analyze this dependency, the near-surface wind speed U_0 is removed from the perturbed parameters and Sobol' indices are estimated for different wind levels varying between 0 and 20 m s^{-1} (the mean ROS within the ensemble changes from 0.39 to 3.82 m s^{-1}). We focus the sensitivity analysis on the eight most influential parameters identified in the previous steps (the near-surface wind speed U_0 is no longer included in the perturbed parameters to generate the N samples). Figure 2 presents Sobol' first-order indices obtained for the different wind levels. Results confirm that the order of importance of the input parameters largely depends on the wind level. Without wind, more than 60% of the ROS variability is explained by two parameters, the fuel layer height e and the ignition temperature T_i. When the wind speed increases, for instance for U_0 = 5 m s^{-1}, the fuel layer height e is far less important (4%), and the leaf area index LAI becomes very influential (41%). This is consistent with Balbi's ROS parameterization. First, the parameter e is only involved in the radiation submodel to estimate the radiant panel size, and radiation is assumed to be independent of the wind speed. Second, as part of the definition of the upward velocity of the combustion gases, the parameter LAI is involved in the tilt angle estimation that depends on the wind speed. This study indicates that the most influential parameters that are relevant to perturb to generate an ensemble depend on the portion of the fire front that is considered (head, flanks or back).

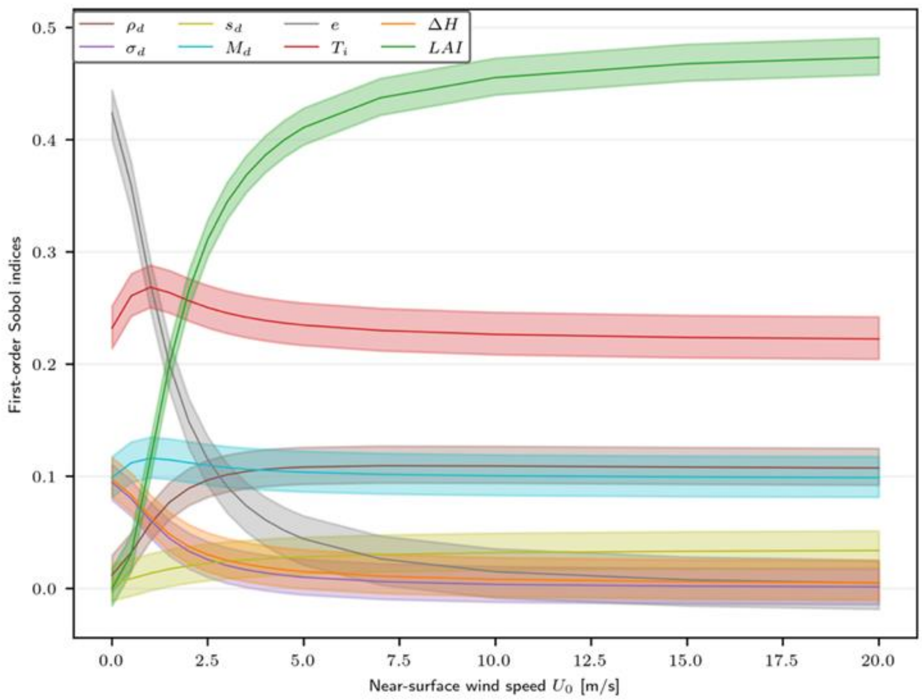

Figure 2- First-order Sobol' indices relating the ROS and 8 perturbed inputs, which are obtained for different levels of the near-surface wind speed U_0. One input parameter corresponds to one color. Shaded intervals represent estimation uncertainties.

4. Conclusions

This study identifies the most influential parameters involved in Balbi's ROS parameterization through Sobol'-Saltelli sensitivity analysis approach to estimate the first- and total-order Sobol' indices. The most influential parameter is the near-surface wind speed U_0. The influence of the other parameters depends on the value of the near-surface wind speed U_0, but overall, the five most influential fuel parameters are the leaf area index LAI, the ignition temperature T_i, the fuel layer height e, the dead fuel particle mass density ρ_d, and the dead fuel moisture content M_d. The next step is to extend this sensitivity analysis approach to a coupled atmosphere/fire model to represent the spatio-temporal impact of input parameters on the wildland fire behavior. This will provide access to the fire-induced wind and to the temporal and spatial variability of the near-surface wind speed, which in turn has an influence on the spatial and temporal variability of the fire front. This will also be helpful to define a protocol for generating a perturbed-physics ensemble and estimating the range of plausible wildland fire behavior for a given event. For this purpose, the sensitivity analysis approach will include different ROS parameterizations and different environmental conditions to go beyond the conditions of a flat grass fire experiment, and thus have sensitivity analysis results that cover a wider range of wildland fire conditions.

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