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Surrogate-based analysis of turbulence and fire-spotting in wild-land fire modelling

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Introduction

Fire-spotting is a harmful phenomenon that accelerates the rate of the spread of fire by producing new independent ignitions by burning embers. It is a multi-scale and a multi-physics phenomena, and the models that try to predict it depends on a wide range of parameters subject to lack of knowledge and/or randomness. In this work we shall

- Perfom a surrogate analysis of a Fire Spotting model introduced in [1] by the means of Polynomial Chaos (PC) and Gaussian Processes (GP);
- Perform Variance-based Sensitivity Analysis and Uncertainty Quantification on the output.

Fire-spotting and Turbulence

The firebrand landing distribution $q(\ell)$ is defined by a lognormal distribution as follows:

$$q(\ell) = \frac{1}{\sqrt{2\pi}\sigma\ell}\exp\frac{-(\ln \ell/\mu)^2}{2\sigma^2}.$$

- μ is the ratio between the square of the mean of landing distance ℓ and its standard deviation, [3],
- σ is the standard deviation of the fire-spotting distribution improving [3].

Here we have some analytical representations:

$$\sigma = \frac{1}{2z_p}\ln\left(\frac{U^2}{rg}\right),$$

$$\mu = \overline{\nu}H_{\max}\left(\frac{3\rho C_d}{2\rho_f}\right)^{1/2},$$

$$H_{\max} = \alpha H_{abl} + \beta\left(\frac{I}{d\,P_{f0}}\right)^{\gamma}\exp\left(\delta\,\frac{N_{FT}^2}{N_0^2}\right),$$

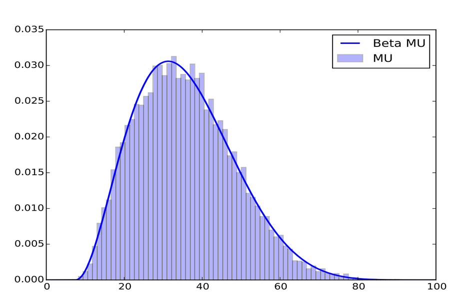
where $H_{\max}$ is the maximum loftable height, $\overline{\nu}$ is an inertial correction for the firebrand, ρ_f is the fuel density, ρ is the ambient air mass density, C_d is the drag coefficient, U is the wind velocity, r is the firebrand radius, g is the gravitational acceleration, $\alpha, \beta, \gamma, \delta$ are empirical constants, $P_{f0} = 10^6 W$ is the reference fire power, H_{abl} is the height of the atmospheric boundary layer, N is the Brunt Väisälä frequency and subscript FT refers to the free troposphere.
Turbulence is modelled via a Gaussian Distribution having parameter D, given by

$$D \simeq 0.1\,\chi\,[\gamma\,\Delta T\,g\,h^3/(\nu\chi)]^{1/3} - \chi,$$

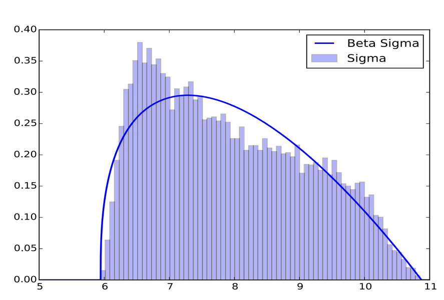
With χ the thermal diffusivity of the air at ambient temperature , γ the thermal expansion coefficient, ΔT the temperature difference of the convective cell.

Computing Priors for input parameters

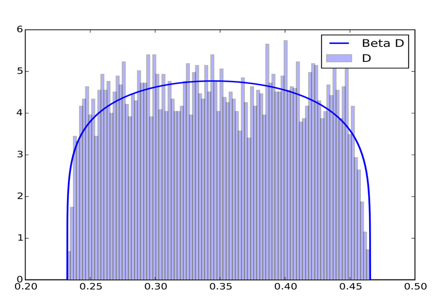
μ, σ and D depend themselves on a large set of sub-parameters. The ones affected by uncertainties are perrturbed around their nominal literature values and a MC simulation is pursued, in order to have Prior distributions. The results are fitted with Beta Distributions.



(a) Fit for μ



(b) Fit for σ



(c) Fit for D

Histograms for Mu, Sigma , D and their respective fits with Beta Distributions.

Workflow

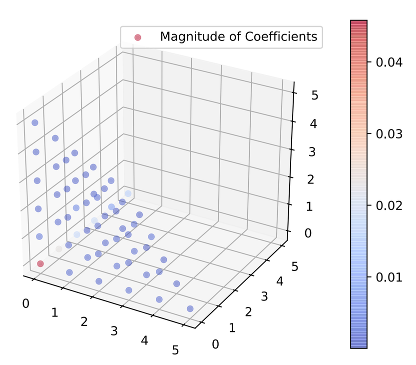
After determining the PDF of the three parameters, here is the followed workflow:

- Sampling with Low Discrepancy Sequences two databases of triples (μ, σ, D), one for training and the other for cross validation;
- Running the WLF simulator for each sampled triple and collect Quantities of Interests (QoI): e.g. Burnt Area at time $t = T$;
- Creating a Surrogate Model for selected QoI h with a weighted finite sum of basis functions:

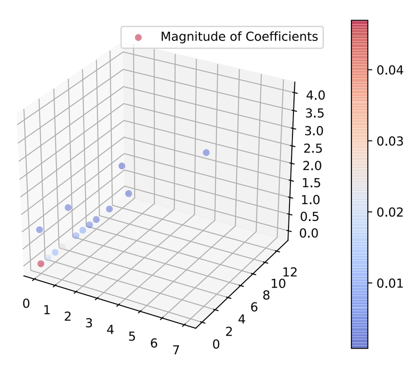
$$h_i^*(x) = \sum_{i=0}^{r}\gamma_i\,\Psi_i(x)\,.$$

  The functions Ψ_i can be of different shape according to the type of algorithm (e.g., PC or GP based);
- Compute the coefficients γ_i through regression or projection schemes. LAR-based sparse algorithm for PC are adopted (see [2]);
- Use the surrogate as a simulator to compute Sobol' Coefficient for the inputs and QoI statistics.

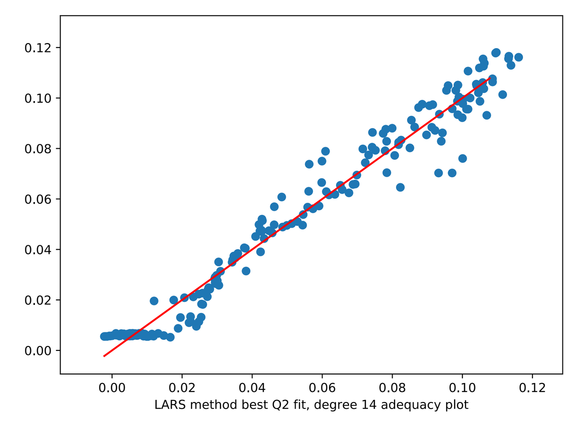
Results



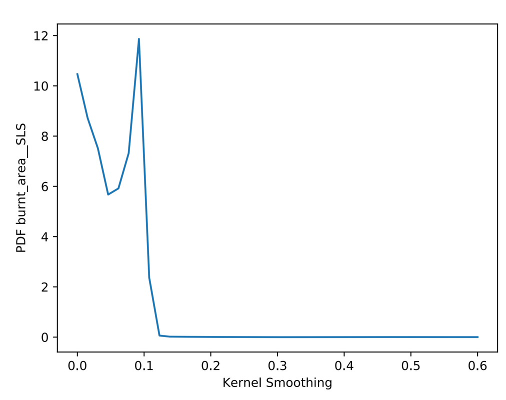
Standard Least Square Coefficients



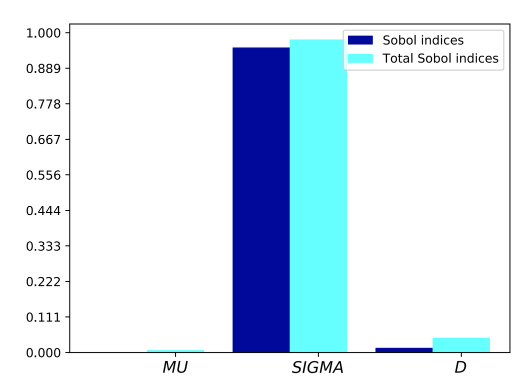
Sparse Algorithm (LAR) for coefficients



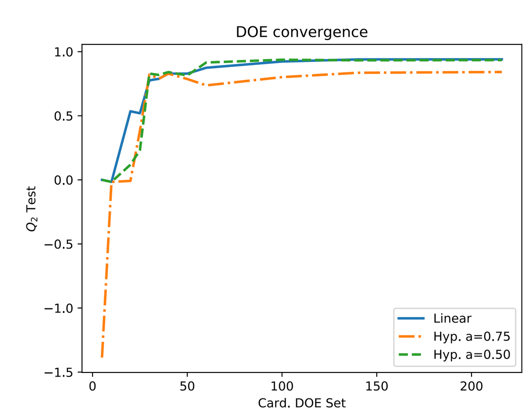
Adequacy plot for LAR



UQ: PDF of Burnt Area



SA: Sobol' indices



Use of secondary database for cross-validation

Conclusions

- The most influential parameter in determining burnt area under uncertainties is σ, related to the *ballistic trajectory* of embers.
- Sparse algorithms for PC allow to attain high degree polynomials while mantaining low the computational budget.
- Different algorithms can lead to the same overall accuracy but may filter out in different way the less influential variables.

References

[1] G. Pagnini, A. Mentrelli, Modelling wildland fire propagation by tracking random fronts, Natural Hazards and Earth System Sciences 14 (8) (2014) 2249–2263.

[2] G. Blatman, B. Sudret, Adaptive sparse polynomial chaos expansion based on least angle regression, Journal of Computational Physics 230 (6) (2011) 2345–2367.

[3] I. Kaur, G. Pagnini, Fire-spotting modelling and parametrisation for wild-land fires, in Proceeding of the 8th International Congress on Environmental Modelling and Software, Toulouse, France, 10–14 July (2016), pp. 384 – 391, ISBN: 978-88-9035-745-9.

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