Global Sensitivity Study in Wildfire Modeling with FDS

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Abstract

Wildfire spread predictions depend on numerous environmental and fuel parameters whose influence may vary among different modeling approaches. This study investigates whether sensitivities identified with the semi-empirical Rothermel-Albini fire spread model remain transferable among different modeling tools and how increasing physical coupling affects parameter importance. Global sensitivity analyses are performed using Borgonovo's Delta index (Borgonovo, 2007) and variance-based Sobol indices for the semi-empirical formulation (Andrews, 2018). The resulting rankings are compared with Delta-based analyses of the Fire Dynamics Simulator (FDS) (McGrattan, Hostikka, Floyd, McDermott, Vanella, Mueller and Paul, 2013b) using two level-set formulations (LS1 and LS4) with different degrees of physical coupling.

The analysis considers the 1-hour dead fuel class and sample-size convergence assessments were performed to evaluate the stability of the dominant sensitivity rankings. FDS simulations are based on the CSIRO F19 grassland benchmark (Cheney, Gould and Catchpole, 1993) and evaluated using average spread speed and burned-area growth. In total, 17,280 simulations were prepared, of which 98.0% were successfully completed.

Both Delta and Sobol analyses identify midflame wind velocity (U) as the dominant parameter, followed by fuel bed depth (δ) and surface-area-to-volume ratio (σ). These dominant sensitivities remain largely transferable to FDS. Compared with the semi-empirical model, fuel bed depth gains importance, whereas surface-area-to-volume ratio decreases. Increasing physical coupling primarily modifies the relative importance of secondary parameters, while LS4 shows stronger wind influence, particularly for burned-area growth. In general, semi-empirical sensitivity analysis reliably identifies dominant wildfire spread parameters, while CFD refines their relative importance through additional physical interactions.

1 Introduction

Wildfires constitute a major and increasingly consequential natural hazard, with effects extending across ecosystems, infrastructure, public health, economic activity, and human safety. Recent evidence indicates that climate change has increased the likelihood of extreme regional fire years in many parts of the world, while longer fire seasons, recurrent drought conditions, and the continued development of fire-prone landscapes further increase exposure and potential losses (Abatzoglou, Kolden, Cullen, Sadegh, Williams, Turco and Jones, 2025; Moore, 2019; United Nations Committee of Experts on Global Geospatial Information Management, 2026). These developments create a growing need for reliable tools that can support wildfire risk assessment, emergency response, fuel-management planning, and the evaluation of alternative mitigation strategies.

Predicting wildfire development remains challenging because fire spread emerges from interacting processes between strongly different spatial and temporal scales. Fuel structure and

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moisture, terrain, wind, combustion, heat transfer, and atmospheric flow can all influence the motion and shape of the fire front. At the same time, many of these quantities are spatially heterogeneous, temporally variable, or imperfectly known. Wildfire spread models therefore necessarily simplify parts of the underlying system, and the appropriate degree of simplification depends on the intended application.

Wildfire models are commonly classified as empirical, semi-empirical, reduced-physics, or fully physics-based approaches (Balbi, Morandini, Silvani, Filippi and Rinieri, 2009). Empirical and semi-empirical models are generally computationally efficient and are therefore suitable for operational applications and large ensembles. In contrast, physics-based modeling frameworks resolve additional processes such as turbulent fluid flow, combustion, and convective and radiative heat transfer, while empirical or semi-empirical submodels may be coupled to represent processes that are not explicitly resolved. This coupling allows interactions between the fire and the surrounding atmosphere to be represented but requires substantially greater computational resources. These modeling categories should not be viewed as strictly competing alternatives. Rather, they provide different balances between computational cost, physical detail, data requirements, and predictive scope.

One of the most influential semi-empirical approaches is the surface fire spread model developed by Rothermel (Rothermel, 1972) and subsequently incorporated into numerous research and operational systems. The formulation estimates the forward rate of spread from fuel properties, fuel moisture, wind, and terrain slope, and remains a foundation of many fire-behavior applications (Andrews, 2018). Its computational efficiency makes it particularly suitable for scenario analysis and operational decision support.

However, the model contains a relatively large number of input variables connected through nonlinear relationships. Consequently, uncertainty or variability in parameters such as wind speed, fuel moisture, fuel-bed depth, fuel loading, and surface-area-to-volume ratio can lead to substantial changes in predicted fire behaviour (Jolly, 2007; Ervilha, Pereira and Pereira, 2017).

Sensitivity analysis provides a systematic means of determining how variations in model inputs contribute to variations in model outputs. Previous wildfire studies have investigated parameter importance using both local and global sensitivity approaches. Jolly et al. (Jolly, 2007) showed that the sensitivity of predicted fire behavior to live fuel moisture strongly depends on the considered fuel model, with grass fuels and particularly dynamic fuel models exhibiting high sensitivity. Salvador et al. (Salvador, Piñol, Tarantola and Pla, 2001) applied global sensitivity analysis to a Mediterranean shrubland fire-propagation model and identified several parameters, including low heat content, particle density, and mineral content, as having only minor influence on the predicted spread rate. Subsequent studies further demonstrated that sensitivity patterns vary with the considered fuel representation and analysis method. Liu et al. (Liu, Hussaini and Ökten, 2015a) found substantial differences in parameter importance among six standard fuel models, while wind, fuel-bed depth, and low heat content were among the influential parameter groups across several of the investigated cases. Ervilha et al. (Ervilha et al., 2017) identified midflame wind speed as the dominant contributor to rate-of-spread uncertainty in one of their investigated scenarios and demonstrated that polynomial-chaos-based uncertainty quantification can reproduce sensitivity information at substantially reduced computational cost. More recently, KC et al. (KC, Aryal, Garg and Hilton, 2021) compared four global sensitivity methods and found dead-fuel moisture and wind speed to be the two most influential parameters for the Rothermel model, while also showing that the choice of sensitivity method involves a trade-off between computational cost, convergence, and the level of sensitivity information obtained.

In parallel, uncertainty-quantification studies have investigated how uncertain fuel and environmental inputs propagate into wildfire spread predictions. Liu et al. (Liu, Tong, Zhang and Song, 2023), for example, treated fuel load, fuel moisture, and wind speed as stochastic variables in a Monte Carlo analysis of large-scale grassland fire spread. Their simulations showed that accounting for these input uncertainties provided a range of possible fire-spread predictions

that contained 75% of the observed spread rates when using their updated grassland fire model, compared with 58.3% for the original model. Such approaches characterize the resulting uncertainty in predicted fire behavior, whereas global sensitivity analysis additionally attributes output variability to individual input parameters. Collectively, previous studies indicate that parameter importance is not universal, but depends on the governing model formulation, considered parameter ranges and probability distributions, selected output quantities, and sensitivity method.

Global sensitivity analysis is particularly useful for nonlinear models because all investigated inputs are varied over their prescribed ranges instead of only around a nominal operating point. Variance-based Sobol indices quantify the contribution of individual parameters and their interactions to output variance, whereas Borgonovo's Delta index measures changes in the complete output distribution and is therefore not restricted to a variance-based interpretation (Saltelli, 2002; Borgonovo, 2007). Combining both approaches provides complementary information on parameter sensitivities, but also requires a larger number of model evaluations. Applying both approaches provides complementary information and allows the robustness of the resulting sensitivity structure to be assessed across methodologically different importance measures.

Although semi-empirical models are well suited to extensive parameter studies, they cannot explicitly represent many spatial and physical mechanisms relevant to wildfire development. Physics-based computational fluid dynamics models provide an alternative framework in which combustion, heat transfer, and fluid flow can be coupled within a three-dimensional domain, allowing the interaction between fire-induced heat release and the surrounding flow field to be represented. In wildfire applications, the moving fire perimeter is frequently represented using a level-set method, in which the front is propagated across an Eulerian grid according to a locally calculated spread rate. Level-set approaches offer an efficient means of representing front deformation, merging, and multidirectional propagation while retaining a tractable description of the fire perimeter (Mallet, Keyes and Fendell, 2009; Lautenberger, 2013).

The Fire Dynamics Simulator (McGrattan et al., 2013b) and its wildland fire extensions can combine computational fluid dynamics with level-set-based surface fire propagation. In this approach, the fire front is represented implicitly by a level-set function and propagated across the fuel surface according to a prescribed rate-of-spread formulation. Because this spread-rate formulation is based on the Rothermel model, common environmental and fuel parameters can be used in both the semi-empirical model and the FDS simulations. The comparison therefore represents different levels of model complexity within a common Rothermel-based propagation framework rather than a comparison of entirely independent fire-spread models

Vanella et al. (Vanella, McGrattan, McDermott, Forney, Mell, Gissi and Fiorucci, 2021) distinguish several implementations of the level-set approach that differ in the degree of coupling between fire-front propagation, the local wind field, and fire-induced flow. In the present study, two of these formulations are considered. In LS1, only the level-set calculation is performed, using a constant and uniform prescribed wind field and slope, without coupling the propagating front to an explicitly simulated fire. In LS4, the wind and fire are fully coupled: the local wind field is used in the rate-of-spread calculation, while the advancing level-set front initiates burning and heat release at newly reached surface cells. The resulting fire-induced changes in the flow field can therefore affect the subsequent fire spread. This hierarchy is particularly useful for examining whether parameter sensitivities established in an empirical spread model remain valid when additional numerical and physical interactions are introduced. Related level-set studies have also demonstrated that wildfire predictions can respond strongly to the quality and resolution of real-world fuel, terrain, and meteorological input data (Purnomo, Zamanialaei, Earle, Theodori, Qin, Lautenberger, Trouvé and Gollner, 2026).

Sensitivity analysis has previously been applied to FDS mainly in building-fire and industrial-fire contexts. Brohus et al. (Brohus, Nielsen, Petersen and Sommerlund-Larsen, 2007) applied the Morris method to an FDS compartment-fire benchmark and found substantial sensitivity

to both physical and numerical input parameters, with the relative importance of individual parameters depending on the considered output. Kelsey et al. (Kelsey, Gant, McNally and Betteridge, 2014) applied global sensitivity analysis to large LNG fire plumes and identified fire diameter as the dominant influence on both flame height and entrainment velocity, while the importance of secondary parameters depended on the considered output. Quaresma et al. (Quaresma, Hehnen and Arnold, 2024) used Sobol indices to compare the sensitivity of FDS Cone Calorimeter and horizontal flame-spread simulations to the same set of material properties. Their results showed substantial differences in parameter importance between the two configurations: whereas the Cone Calorimeter response was dominated by strong interactions between temperature-dependent specific-heat values, the rate of spread was primarily influenced by PMMA emissivity and specific heat at elevated temperature. This demonstrated that parameter sensitivities identified in one simulation configuration are not necessarily transferable to another. More recently, Brännström et al. (Brännström, Jamil, Nouroozyan and Sailer, 2025) highlighted the sensitivity of fire-spread simulations to model assumptions, numerical methods, and uncertain input quantities across different scales. In their wildfire example, different spatial representations of an otherwise comparable tree fuel load resulted in substantial differences in the predicted heat-release-rate evolution, illustrating the importance of adequately characterizing uncertain model inputs in physically detailed fire simulations. In the wildfire context, Valero et al. (Valero, Jofre and Torres, 2021) combined uncertainty quantification and sensitivity analysis with multifidelity WFDS simulations. Their analysis identified fuel moisture, fine fuel load, and wind speed as the largest contributors to the variability in fire rate of spread, followed by fuel-bed depth and the fuel-particle surface-area-to-volume ratio. By reducing the computational cost by more than two orders of magnitude compared with straightforward Monte Carlo sampling, their study further demonstrated the feasibility of sensitivity analysis for computationally expensive wildfire CFD simulations.

Nevertheless, an important question remains regarding the transferability of parameter sensitivities across model-complexity levels. Sensitivities obtained from the semi-empirical Rothermel formulation cannot automatically be assumed to remain unchanged when the same inputs are introduced into a three-dimensional CFD environment. Increased physical coupling may preserve the dominant drivers while redistributing the importance of secondary parameters or may produce different sensitivity structures for directional spread and spatial fire growth. In particular, it remains insufficiently understood whether the increasing degree of physical coupling from LS1 to LS4 affects the inferred importance of environmental and fuel parameters.

The present study addresses this question by applying a common sampling design to a direct evaluation of the semi-empirical Rothermel-Albini implementation and to two FDS level-set formulations representing different degrees of physical coupling. The semi-empirical model is first evaluated using Borgonovo Delta and Sobol total-effect indices for the 1-hour dead fuel class. Convergence analyses are used to determine whether the resulting sensitivity estimates and parameter rankings are stable with increasing sample size. The same parameter combinations are then transferred to FDS and evaluated using LS1 and LS4. LS1 provides a comparatively idealized level-set representation dominated by prescribed spread-rate relationships, whereas LS4 additionally couples fire propagation with combustion, heat release, and the evolving flow field.

The simulations use the spatial configuration of the CSIRO F19 grassland fire experiment as a controlled reference case (Cheney et al., 1993; Cheney, Gould and Catchpole, 1998; McGrattan, Hostikka, Floyd, McDermott, Vanella, Mueller and Paul, 2013a). Sensitivities are evaluated for both average forward spread speed and burned-area growth, thereby distinguishing directional propagation from multidirectional fire development. In total, 17280 FDS simulations were prepared across the two level-set formulations.

The objectives of this work are therefore to: (i) identify robust dominant parameters in the semi-empirical Rothermel-Albini formulation using complementary global sensitivity measures,

(ii) assess whether the direct evaluation sensitivity structure transfers to a three-dimensional CFD-based fire-spread model, and (iii) determine how increasing physical coupling from LS1 to LS4 modifies the relative importance of wind, terrain, and fuel properties. Through this comparison, the study clarifies which sensitivities remain stable across modeling approaches and which emerge or change as additional physical and numerical interactions are introduced.

2 Fire Spread Modeling Framework

The modeling framework combines an semi-empirical surface-fire spread formulation with two level-set implementations in the Fire Dynamics Simulator (FDS). This hierarchy enables the parameter sensitivities obtained from a computationally inexpensive semi-empirical model to be compared with those obtained after introducing progressively stronger physical coupling within a three-dimensional CFD environment.

2.1 Semi-Empirical Rothermel-Albini Formulation

The semi-empirical model is based on the Rothermel surface-fire spread formulation and its subsequent developments, as summarized by Andrews (Andrews, 2018). The model estimates the forward rate of spread of a surface fire from fuel-bed properties, fuel moisture, wind, and terrain slope. The metric implementation used in this study follows the complete calculation chain presented in Appendix A and provides the rate of spread, reaction intensity, and fireline intensity for each sampled parameter combination.

The forward rate of spread is calculated as

$$R = \frac{I_R \, \xi \, (1 + \phi_W + \phi_S)}{\rho_b \, \epsilon \, Q_{ig}}, \tag{1}$$

where R is the forward rate of spread, I_R is the reaction intensity, ξ is the propagating-flux ratio, ϕ_W and ϕ_S are the wind and slope correction factors, respectively, ρ_b is the oven-dry bulk density, ϵ is the effective heating number, and Q_{ig} is the heat of pre-ignition.

The formulation describes fire spread through nonlinear interactions between fuel, moisture, wind, and terrain variables. The input parameters are sampled independently within their prescribed ranges and no statistical dependencies between the parameters are imposed through the sampling procedure. Investigated inputs include the low heat content h, total mineral content S_t, effective mineral content S_e, oven-dry particle density ρ_p, surface-area-to-volume ratio σ, oven-dry fuel load w_0, fuel-bed depth δ, moisture of extinction M_x, fuel moisture content M_f, wind velocity at midflame height U, and terrain slope steepness $\tan(\phi)$. The ranges assigned to these variables are presented in Section 3 and were selected using values and recommendations reported by Andrews (Andrews, 2018) and Liu et al. (Liu, Jimenez, Hussaini, Ökten and Goodrick, 2015b).

The semi-empirical formulation represents the reference model in the present study. Because it can be evaluated at negligible computational cost relative to CFD, it allows extensive sampling and convergence assessment before the same parameter combinations are transferred to FDS.

2.2 Level-set fire propagation in FDS

The three-dimensional simulations were performed with FDS version 6.9.1 (McGrattan et al., 2013b). In the level-set approach, the fire perimeter is represented implicitly as the zero contour of a scalar field. The front is propagated through an Eulerian grid according to a locally defined spread velocity, allowing deformation, merging, and multidirectional movement of the fire perimeter without explicitly tracking individual marker particles. (Mallet et al., 2009; Lautenberger, 2013).

Within the FDS wildland-fire framework, the level-set spread rate is linked to the Rothermel formulation. This connection allows the same environmental and fuel-related input parameters to be used in both the semi-empirical Rothermel model and the FDS simulations. Consequently, the comparison does not involve independent fire-spread formulations, but rather different representations and levels of physical coupling within a common Rothermel-based propagation framework.

FDS provides several level-set configurations that differ in the degree of coupling between the moving fire front, combustion, heat release, terrain, and the surrounding flow field (Vanella et al., 2021). The present study considers LS1 and LS4 because they represent two limiting levels of model complexity.

In LS1, the fire front is propagated kinematically using the prescribed spread-rate formulation together with the imposed wind and slope conditions. Combustion-generated heat release and fire-induced modifications of the flow field do not feed back onto the propagation process. LS1 therefore provides the closest FDS counterpart to the semi-empirical Rothermel-Albini calculation, while additionally representing the spatial development of the fire perimeter on the numerical grid.

In LS4, level-set propagation is coupled with combustion, heat release, and the evolving three-dimensional flow field. Fire spread can therefore be influenced not only by the prescribed environmental and fuel parameters but also by interactions among buoyancy, turbulence, heat transfer, and fire-induced motion. LS4 represents the most strongly coupled formulation considered in this study. Consequently, individual input parameters may affect the predicted spread rate through multiple pathways. For example, terrain slope enters the prescribed spread-rate formulation directly while also modifying the resolved flow field in LS4. Such overlapping pathways may amplify the apparent influence of individual parameters and are therefore considered when interpreting the sensitivity results.

Comparing LS1 and LS4 makes it possible to determine whether increasing the physical coupling changes the sensitivity structure inherited from the semi-empirical model. Similar parameter rankings would indicate that the dominant controls are robust across model-complexity levels, whereas systematic differences would reveal sensitivities introduced or redistributed by CFD coupling and the numerical representation of the fire front. Intermediate level-set modes were not considered to maintain a focused comparison between the weakly and strongly coupled limiting cases.

3 Global Sensitivity Analysis

The global sensitivity analysis was restricted to the 1-hour dead fuel class, which also serves as the basis for subsequent FDS simulations. This restriction ensures methodological consistency between the semi-empirical Rothermel-Albini model and the CFD-based simulations while focusing on the fuel class that exhibits sustained fire spread within the investigated simulation time. Consequently, all directly evaluated and CFD-based sensitivity results presented in this study refer to the same underlying fuel class.

Eleven input parameters were treated as statistically independent random variables with uniform probability distributions. The investigated variables comprise low heat content h, total mineral content S_t, effective mineral content S_e, oven-dry particle density ρ_p, surface-area-to-volume ratio σ, oven-dry fuel load w_0, fuel-bed depth δ, moisture of extinction M_x, fuel moisture content M_f, wind velocity at midflame height U, and terrain slope steepness $\tan(\phi)$.

The parameter ranges are summarized in Table 1. The selected intervals are based on the comprehensive parameter compilation of Andrews (Andrews, 2018) and are further guided by the sensitivity-study parameterization proposed by Liu et al. (Liu et al., 2015b). Together, these sources provide physically realistic bounds while ensuring stable sampling over the investigated parameter space.

Table 1: Sampling ranges for the 1-hour fuel class used in the global sensitivity analysis.

Symbol	**Description**	**Range**
h	Low heat content	13,956–27,912
S_t	Total mineral content	0.030–0.0555
S_e	Effective mineral content	0.010–0.015
ρ_p	Oven-dry particle density	480–737
σ	Surface-area-to-volume ratio	24.6–114.8
w_0	Oven-dry fuel load	1.064–1.176
δ	Fuel-bed depth	0.15–1.83
M_x	Moisture of extinction	0.12–0.40
M_f	Fuel moisture content	0.076–0.084
U	Wind velocity at midflame height	0–322
$\tan(\phi)$	Terrain slope steepness	0–0.268

Parameter combinations were generated using the Saltelli sampling scheme (Saltelli, 2002) implemented in SALib, with second-order sampling enabled. Eleven statistically independent input parameters were considered. For this configuration, the total number of model evaluations is given by $N(2D+2)$, where N denotes the base sample size and $D = 11$ is the number of input parameters.

For the direct Rothermel-Albini model, separate Saltelli sampling sets were generated for increasing base sample sizes from $N = 20$ to $N = 500$, in increments of 20. Each sampling set was evaluated separately to investigate the convergence of the Delta and Sobol sensitivity indices. The largest sampling set comprised 12,000 model evaluations. The sampling sets were generated by repeated calls to SALib's Saltelli sampler with different base sample sizes, without independently randomized sampling realizations. The convergence assessment therefore evaluates the stability of the sensitivity estimates across separately generated sampling configurations, rather than variability across statistically independent sampling replicates.

For the cross-model comparison, the parameter combinations generated with $N = 360$, corresponding to 8,640 model evaluations, were exported and transferred without modification to FDS. Each of these 8,640 parameter combinations was evaluated using both LS1 and LS4. Thus, the direct Rothermel-Albini evaluation and both FDS formulations were based on the same original parameter combinations for the cross-model sensitivity comparison.

Due to the computational cost of FDS, its convergence assessment followed a different approach. Rather than generating and simulating new sampling sets for each sample size, progressively larger nested subsets of the existing $N = 360$ ensemble were analyzed. Consequently, the Rothermel convergence study was based on separately generated sampling sets, whereas the FDS convergence study assessed the stability of sensitivity estimates within a single existing sampling sequence.

Two complementary global sensitivity measures were applied using the open-source Python library SALib (Herman and Usher, 2017). Borgonovo's Delta index (Borgonovo, 2007) was selected as the primary sensitivity metric because it can be consistently evaluated for both the semi-empirical Rothermel model and the FDS simulations. Delta is a moment-independent measure based on the difference between the unconditional output distribution and the corresponding conditional distributions obtained for a given input parameter. It therefore captures parameter influence beyond changes in individual statistical moments such as the mean or variance.

In addition, variance-based Sobol total-effect indices were computed for the Rothermel model. In contrast to Delta, Sobol indices decompose the output variance and attribute fractions of this variance to individual input parameters and their interactions. The total-effect index S_T accounts for both the first-order contribution of a parameter and all higher-order in-

teractions involving that parameter. Only S_T is considered because the objective of the present study is to rank parameters according to their overall contribution to output variability, including interaction effects, rather than to decompose this contribution into direct and interaction components. This provides a comprehensive variance-based measure for comparison with the moment-independent Delta ranking.

Sensitivity indices were calculated using SALib. For the directly evaluated Rothermel-Albini model, Borgonovo Delta indices and Sobol total-effect indices were estimated from the sampled model responses. The Sobol analysis used the second-order Saltelli sampling configuration. For FDS, Borgonovo Delta indices were estimated from the available valid input-output pairs. The Delta estimator does not require the complete structured Saltelli evaluation matrix used by the Sobol estimator and can therefore be applied after excluding invalid responses. The analyses used 100 resamples and a nominal confidence level of 95% for the Delta estimates. The FDS sensitivity indices were calculated separately for each level-set formulation.

The directly evaluated sensitivity analysis serves two purposes. First, it establishes robust parameter rankings through convergence analyses using both Delta and Sobol sensitivity measures. Second, it provides the reference sensitivity structure against which the CFD-based FDS simulations are compared in the Results section, allowing the transferability of parameter importance from the semi-empirical formulation to progressively more physically coupled fire-spread models to be assessed.

4 FDS Simulation Setup

To investigate whether the sensitivity structure identified for the semi-empirical Rothermel-Albini model is preserved in a physics-based simulation environment, the sampled parameter combinations were transferred to the Fire Dynamics Simulator (FDS), version 6.9.1-55-g307c7a9-master (McGrattan et al., 2013b). The simulations use the spatial extent and general layout of the CSIRO Grassland Fire Experiment F19 from the official FDS validation guide (McGrattan et al., 2013a). Although the benchmark geometry follows the validation case, all fuel properties and combustion-related input parameters were defined specifically for the present sensitivity study.

The computational domain corresponds to the configuration described in the FDS Validation Guide (McGrattan et al., 2013a) and by Vanella et al. (Vanella et al., 2021). The only geometric modification is the slope of the terrain, which is varied systematically throughout the parameter study. The slope is represented by tilting the fuel surface, resulting in an increasing number of vertical grid cells with increasing inclination. To maintain feasible runtimes for the large number of CFD simulations, the maximum terrain slope factor was limited to 15°. A uniform Cartesian mesh with a cell size of 5 m is used for all simulations. Preliminary mesh-sensitivity studies employing finer resolutions showed only minor differences in the predicted rate of spread and burned-area growth. Consequently, the 5 m grid was considered an appropriate compromise between numerical accuracy and computational efficiency.

The wind direction was kept constant and aligned with the positive x-axis, allowing the influence of wind-speed magnitude and terrain slope to be investigated independently. For every sampled parameter combination, two simulations were executed using different level-set formulations: LS1 and LS4. These two formulations represent substantially different levels of physical coupling within the FDS level-set framework. Comparing both formulations therefore allows the influence of increasing physical coupling on the resulting sensitivity structure to be investigated directly. An example of the computational domain is shown in Figure 1.

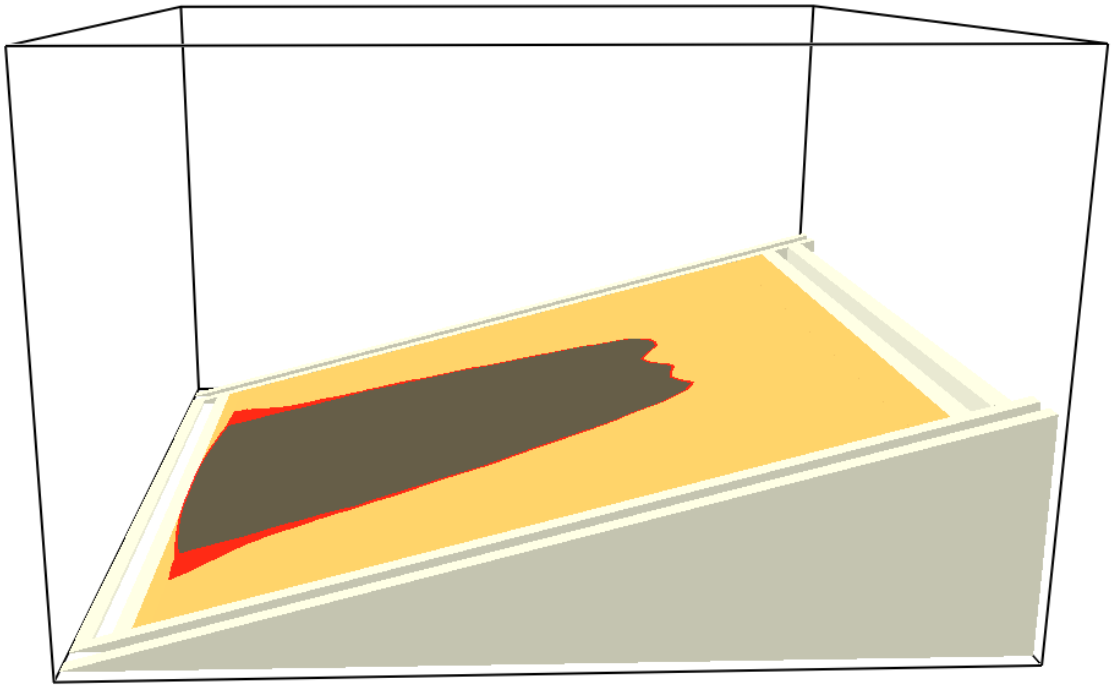


Figure 1: FDS Level Set Simulation with the domain based on the CSIRO Grassland Fire Experiment F19 with inclined terrain.

For the LS4 simulations, FDS was operated using the Simple Very Large Eddy Simulation (SVLES) mode. SVLES was selected to reduce the computational cost of the large simulation ensemble and was retained from the underlying CSIRO F19 validation configuration. Parameters not included in the sensitivity analysis were kept constant across the simulations, while the investigated fuel and environmental properties were varied according to the sampled parameter combinations.

Each simulation is driven by one parameter combination generated from the Saltelli sampling design described in the previous section. These sampled input values are automatically converted into complete FDS fuel definitions. Some quantities required by FDS are not sampled independently but are derived from the sampled Rothermel input parameters. In particular, FDS requires the fuel-bed packing ratio β. To avoid introducing an additional independent parameter, β is calculated for each parameter combination from the sampled oven-dry fuel load w_0, fuel-bed depth δ, and oven-dry particle density ρ_p according to

$$\rho_b = \frac{w_0}{\delta}, \qquad \beta = \frac{\rho_b}{\rho_p}, \tag{2}$$

where w_0 denotes the oven-dry fuel load and δ the fuel-bed depth.

Furthermore, the FDS level-set implementation requires the no-wind, no-slope rate of spread R_0. This quantity is precomputed using the semi-empirical Rothermel model with both wind and terrain effects disabled. Using the same underlying spread formulation ensures methodological consistency between the directly evaluated and CFD-based approaches.

A total of 17,280 simulations were prepared, corresponding to two level-set formulations for every sampled parameter combination. 16,934 simulations completed successfully, corresponding to an overall success rate of 98.0%. The remaining cases terminated during the initialization stage because certain parameter combinations produced non-physical spread-rate predictions within the current implementation of the Rothermel-based level-set model. These failed simulations were excluded from the subsequent postprocessing and sensitivity analysis.

All input files were generated automatically using Python-based workflow scripts and executed on a high-performance computing cluster, enabling the efficient evaluation of the large parameter ensemble required for the global sensitivity analysis.

5 Postprocessing and Metric Extraction

The FDS simulations produce time-resolved level-set fields describing the evolution of the fire front throughout the computational domain. All fire-spread metrics are extracted from a 0.1 m Above Ground Level (AGL) slice, which maintains a constant distance above the locally inclined fuel surface. This evaluation strategy provides comparable measurement conditions for all terrain configurations. From the resulting level-set field, both the forward rate of spread along the x-direction and the burned-area development are determined and subsequently used as response variables for the CFD-based sensitivity analysis. To enable a direct comparison with the directly evaluated Rothermel-Albini model, four quantitative response metrics were extracted from each simulation: average rate of spread, maximum rate of spread, maximum burned area, and mean area growth rate. These quantities subsequently serve as response variables for the CFD-based global sensitivity analysis.

Operational definitions. The fuel patch measures 200×200 m and is discretized into 40×40 cells with a uniform cell size of $\Delta x = 5\,\mathrm{m}$. Ignition is prescribed by a straight ignition line covering 1×10 cells in the y-direction immediately upwind of the fuel bed. To avoid numerical artifacts associated with the prescribed ignition, the transition from the ignition line to the first fuel-cell column is excluded from the spread-rate evaluation. Time measurements therefore begin when the first cell inside the fuel patch ignites.

Fire-front arrival times are obtained from the FDS level-set field, whose values range between -1 and 1. A fuel cell is considered ignited at the earliest instant when the level-set function reaches zero. This zero-crossing provides a consistent and reproducible definition of flame-front arrival throughout all simulations.

Let $i = 1, \ldots, 40$ denote the successive fuel-cell columns in the x-direction, where each column comprises all fuel cells sharing the same x-position across the width of the fuel patch. Let τ_i denote the earliest flame-front arrival time within column i. Furthermore, let $K \leq 40$ denote the farthest ignited column reached within the 180 s simulation period. If the fire front does not traverse the entire fuel patch, only columns up to K are considered in the following calculations.

Cell-to-cell spread speed. For two adjacent fuel-cell columns, the local forward spread speed is defined as

$$v_i = \frac{\Delta x}{\tau_i - \tau_{i-1}}, \tag{3}$$

where Δx is the distance between the neighboring columns. This quantity represents the instantaneous propagation speed between successive fuel-cell columns.

Average rate of spread (Avg Speed). The average forward spread speed is calculated from the total traveled distance divided by the corresponding travel time,

$$\bar{R}_x = \frac{(K-1)\Delta x}{\tau_K - \tau_1}, \tag{4}$$

which provides a robust estimate of the average forward spread speed over the complete traveled distance while reducing sensitivity to local fluctuations in the front position.

Maximum rate of spread (Max Speed). The maximum forward spread speed is defined as

$$R_{x,\max} = \max_{2 \le i \le K} v_i, \tag{5}$$

representing the highest instantaneous cell-to-cell propagation speed observed during the simulation.

Mean area growth rate (Avg Area Growth). In addition to directional fire spread, the spatial development of the burned area was also evaluated. The burned area $A(t)$ is calculated from the number of burned fuel cells $N_b(t)$ identified from the level-set field as

$$A(t) = N_b(t)\,\Delta x\,\Delta y, \tag{6}$$

where $\Delta x \Delta y = 25\,\mathrm{m}^2$ is the area of one fuel cell. Rather than using the complete simulation period, the area growth rate is evaluated between the times when the burned area reaches 5 % and 95 % of the final burned area. The corresponding mean area growth rate is

$$G_A = \frac{A(t_{95}) - A(t_5)}{t_{95} - t_5}, \tag{7}$$

where t_5 and t_{95} denote the times at which 5 % and 95 % of the final burned area A_{final} are reached, respectively. This definition minimizes the influence of ignition transients at the beginning of the simulation and saturation effects once the fire approaches the domain boundaries.

6 Results and Discussion

6.1 Fire-Spread Characteristics of the FDS Simulations

Figure 2 summarizes the distributions of the extracted fire-spread metrics for both investigated level-set formulations and compares the forward spread speeds with the rate of spread obtained from the direct evaluation of the semi-empirical Rothermel-Albini model. The upper panels show the average and maximum forward spread speeds obtained with LS1 and LS4 together with the directly evaluated Rothermel rate of spread, whereas the lower panels present the corresponding mean area growth rates for the two FDS formulations.

Both level-set formulations exhibit comparable median spread speeds, although LS4 produces noticeably broader distributions and larger interquartile ranges than LS1. The direct Rothermel evaluation exhibits an even broader spread-rate distribution, particularly towards high values, with substantially larger upper extremes than those obtained with LS1 and LS4. This indicates that parameter combinations producing very high rates of spread in the semi-empirical formulation do not necessarily result in equally high propagation speeds when implemented within the FDS level-set framework.

The difference between LS1 and LS4 is also evident for the area-based metric, where LS4 shows substantially higher variability. Numerous upper outliers occur across the investigated response metrics. These values correspond to parameter combinations producing exceptionally rapid fire spread within the investigated parameter space and were retained in the subsequent sensitivity analysis. The broader distributions observed for LS4 compared with LS1 indicate a stronger response to certain parameter combinations when additional physical coupling is introduced.

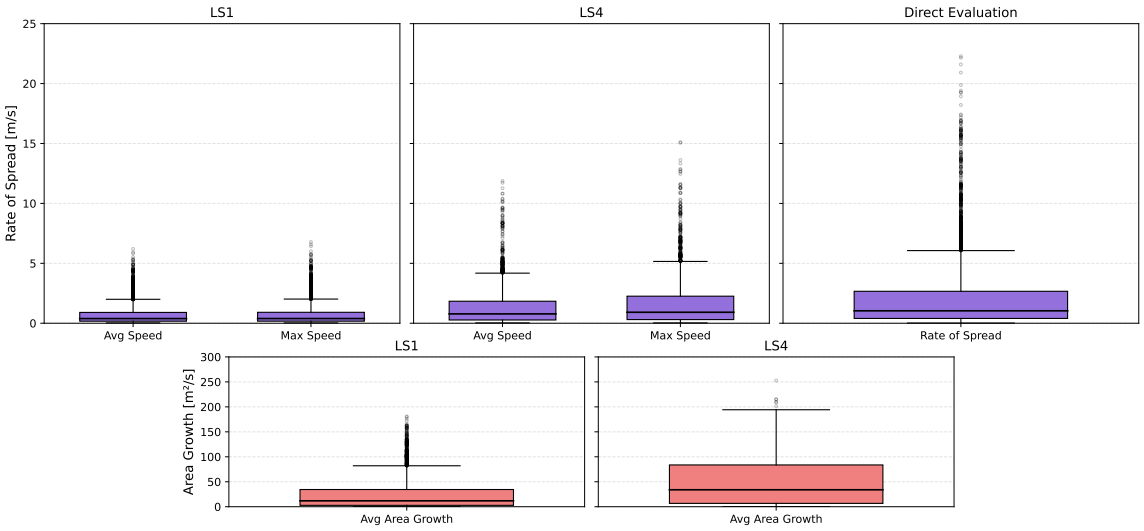


Figure 2: Boxplot comparison of the fire-spread metrics for the 1-hour fuel class. The upper panels show the average and maximum forward spread speeds obtained with LS1 and LS4 and the rate of spread obtained from the direct evaluation of the semi-empirical Rothermel-Albini model. The lower panels show the corresponding mean area growth rates for LS1 and LS4.

6.2 Sensitivity Analysis of the Rothermel-Albini Model

The Rothermel-Albini model was first evaluated using two complementary global sensitivity measures, Borgonovo's Delta index and Sobol total-effect indices. Both methods were applied to the same Saltelli sampling design for the 1-hour dead fuel class, allowing a direct comparison of parameter rankings while minimizing methodological differences between the two approaches.

The objective of this analysis is to establish a robust sensitivity structure for the semi-empirical fire-spread model itself. Second, it provides the reference against which the subsequent CFD-based FDS simulations are evaluated. Since the formulation represents the underlying spread-rate model employed by the FDS level-set implementation, identifying stable parameter rankings is an essential prerequisite for assessing the transferability of sensitivities to increasingly coupled fire-spread simulations.

Particular attention is therefore given to the stability of sensitivity estimates with increasing sample size, to assess whether the identified dominant parameter rankings are sensitive to the number of model evaluations.

6.3 Delta and Sobol Convergence

Figures 3 and 4 summarize the convergence behavior of Borgonovo's Delta indices and Sobol total-effect indices, respectively, for the directly evaluated Rothermel-Albini model. The convergence analysis was performed using progressively increasing sample sizes, ranging from a minimum of 480 to a maximum of 12,000 model evaluations.

Figure 3 shows that the Delta indices exhibit noticeable fluctuations for small sample sizes. As the number of model evaluations increases, the ranking of the dominant parameters becomes progressively more stable. In particular, the relative importance of wind velocity, fuel-bed depth, and surface-area-to-volume ratio shows comparatively limited changes beyond approximately 3,000 model evaluations. Smaller sensitivities remain subject to fluctuations, and the observed stabilization should therefore be interpreted as an empirical convergence assessment rather than proof of numerical convergence.

Throughout the convergence study, wind velocity at midflame height (U) consistently exhibits the highest Delta index, followed by fuel bed depth (δ) and the surface-area-to-volume

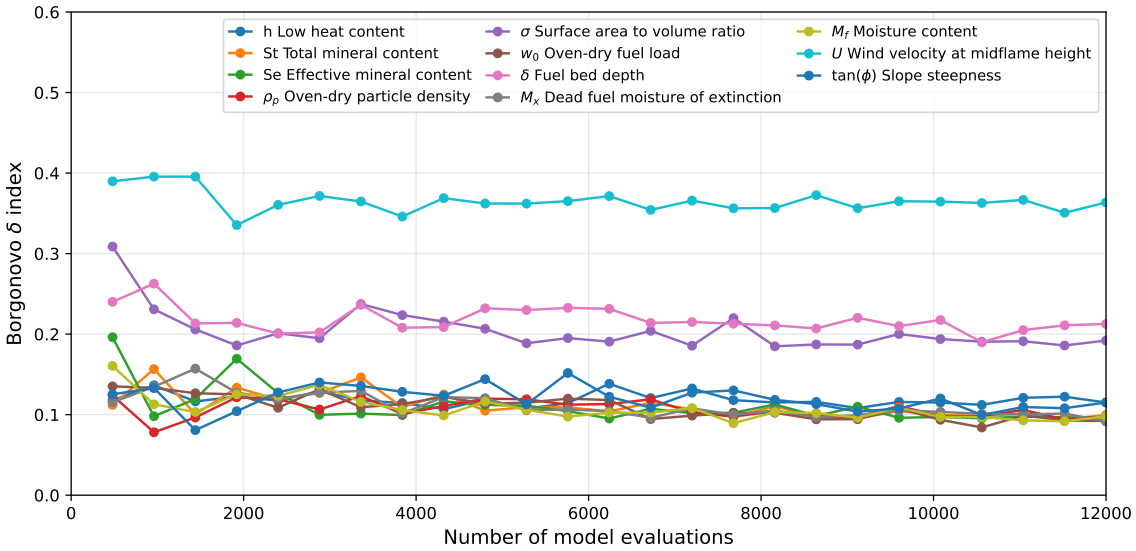


Figure 3: Convergence of δ-sensitivity indices as a function of sample size for the 1-hour fuel class in the Rothermel-Albini model.

ratio (σ). All remaining parameters contribute substantially less to the predicted rate of spread and approach nearly constant sensitivity levels once convergence has been achieved.

The corresponding convergence of the Sobol total-effect indices is shown in Figure 4. In the present analysis, the Sobol total-effect estimates exhibit substantial fluctuations at smaller sample sizes. Nevertheless, the hierarchy of dominant parameter remains unchanged throughout the convergence process.

Both sensitivity measures identify the same three dominant drivers of fire spread. Wind velocity clearly dominates the model response, while fuel bed depth and surface-area-to-volume ratio form a distinct second sensitivity tier. Parameters related to mineral content, fuel moisture, fuel load, particle density, and slope exhibit comparatively small contributions throughout the investigated parameter space.

Although Borgonovo's Delta index and Sobol's total-effect index are based on fundamentally different mathematical concepts, they converge towards nearly identical parameter rankings. Delta quantifies the influence of an input variable on the complete output distribution, meaning that it captures changes not only in the output variance, but also in other distributional characteristics such as its location, shape, and tails. Sobol indices, in contrast, quantify the contribution of individual parameters and their interactions specifically to the output variance. The close agreement between both methods therefore demonstrates that the identified sensitivity structure is robust and largely independent of the selected global sensitivity metric.

Delta is subsequently used as the primary metric for the comparison with FDS because its moment-independent formulation provides a comprehensive characterization of parameter influence across the complete output distribution. Its applicability to both the Rothermel model and the FDS simulations additionally enables a consistent sensitivity metric to be used across both modeling approaches. Sobol indices, in contrast, quantify the contribution of individual parameters and their interactions specifically to the output variance. The Sobol analysis provides a complementary variance-based assessment of the sensitivity ranking obtained from the Delta method.

6.4 Transferability to FDS

The sensitivity analysis of the Rothermel-Albini model establishes a reference parameter hierarchy under the investigated conditions. The next step is to determine whether this sensi-

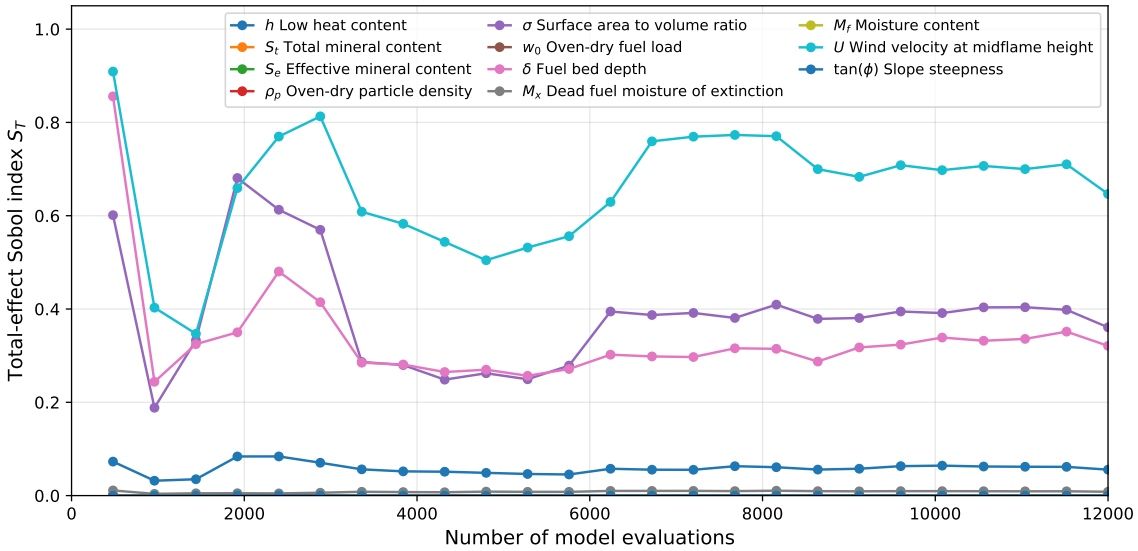


Figure 4: Convergence of total-effect sensitivity indices S_T as a function of sample size for the 1-hour fuel class in the Rothermel-Albini model.

tivity structure is preserved when the same parameter variations are transferred to the three-dimensional FDS framework. This comparison provides a direct assessment of the transferability of parameter importance across increasing levels of physical coupling.

For this purpose, the parameter combinations generated for the directly evaluated global sensitivity analysis were implemented in FDS using the LS1 and LS4 level-set formulations. In contrast to the semi-empirical model, FDS resolves additional physical processes, including combustion, heat release, buoyancy-driven flow, and three-dimensional fire-front propagation. Consequently, the relative influence of individual input parameters may change as additional physical interactions are introduced.

Before comparing the converged sensitivity structures with the direct evaluation, the stability of the FDS-based Delta indices was evaluated.

6.4.1 Convergence of FDS Delta Indices

The convergence of the FDS-based Delta indices was investigated using nested subsets of the existing Saltelli sampling sequence. Nominal base sample sizes of $N = 20, 40, 60, 80, 120, 180, 240, 300,$ and 360 were considered, corresponding to 480–8,640 selected model evaluations before filtering. For each subset, non-numerical or missing responses were excluded separately for the investigated output metric. Consequently, the number of valid input-output pairs used to estimate each Delta index could differ between output metrics and level-set formulations. No independent FDS sampling sequences were generated for this assessment. Delta indices were estimated using 100 resamples and a nominal confidence level of 95%.

Figures 5 and 6 present the convergence behavior for average spread speed using LS1 and LS4, respectively. In both formulations, the dominant parameters show comparatively stable estimates beyond approximately 6,000 valid simulations. Wind velocity at midflame height (U) consistently exhibits the largest Delta index throughout the convergence process, especially with LS4. Fuel bed depth (δ) forms the second sensitivity tier and secondary parameters show larger fluctuations for smaller sample sizes but converge towards stable values as additional simulations are included. For LS1, wind velocity and fuel-bed depth temporarily exhibit similar Delta indices at intermediate sample sizes, but their estimates separate again as the sample size increases.

The available ensembles of approximately 8,450–8,480 valid speed responses suggest comparatively stable rankings of the dominant parameters.

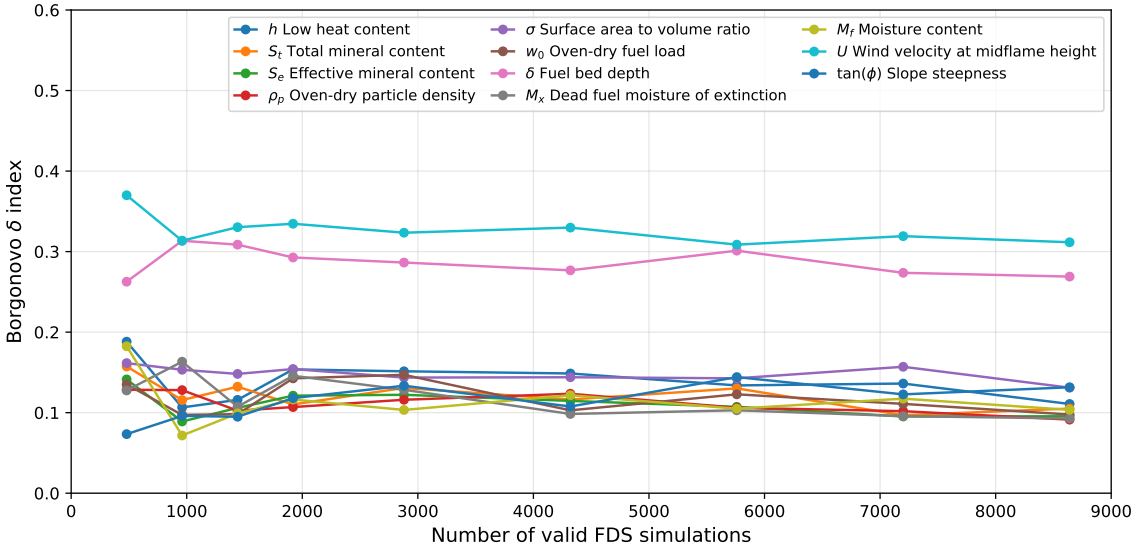


Figure 5: Convergence of Delta indices for LS1 using average spread speed as the output metric.

Figure 7 compares the converged Delta indices obtained from the Rothermel-Albini model with those derived from the FDS simulations. The semi-empirical model is evaluated using the predicted rate of spread, whereas the CFD simulations are analysed using average spread speed and burned area growth.

Across all models and output metrics, wind velocity at midflame height (U) remains the dominant parameter. This consistent ranking indicates that the primary driver of wildfire spread is largely preserved when the analysis is transferred from the formulation to the CFD environment.

The largest differences occur among the secondary parameters. Fuel bed depth (δ) becomes more influential for LS1 than in the direct evaluation and LS4. In contrast, the relative importance of the surface-area-to-volume ratio (σ) decreases in both CFD formulations. While σ directly influences several terms of the Rothermel spread equation, its contribution becomes less dominant once additional physical processes, such as spatial fire growth, combustion, heat transfer, and fluid flow, are explicitly resolved.

Despite these quantitative differences, the overall parameter hierarchy remains remarkably consistent. The semi-empirical model therefore captures the dominant sensitivity structure that is also observed in the considerably more complex CFD simulations.

6.4.2 Influence of the Level-Set Formulation

Although both FDS formulations identify the same dominant parameters, relative sensitivities differ between LS1 and LS4.

LS1 propagates the fire front using the prescribed Rothermel spread rate while neglecting combustion feedback and fire-induced flow. Consequently, its sensitivity structure remains comparatively close to the direct evaluation. Wind velocity and fuel bed depth dominate the response, whereas the remaining parameters contribute only moderately. However, there are noticeable differences between the magnitudes of the dominant drivers.

LS4 introduces a substantially higher degree of physical coupling by combining the level-set propagation with combustion, heat release, and fluid-dynamic feedback. Under this formulation, wind velocity becomes even more dominant, particularly when burned area growth is considered as the response metric. At the same time, the relative importance of several secondary parameters decreases, indicating that additional physical interactions concentrate the overall sensitivity more strongly on the dominant wind forcing.

The comparison demonstrates that increasing model complexity does not fundamentally

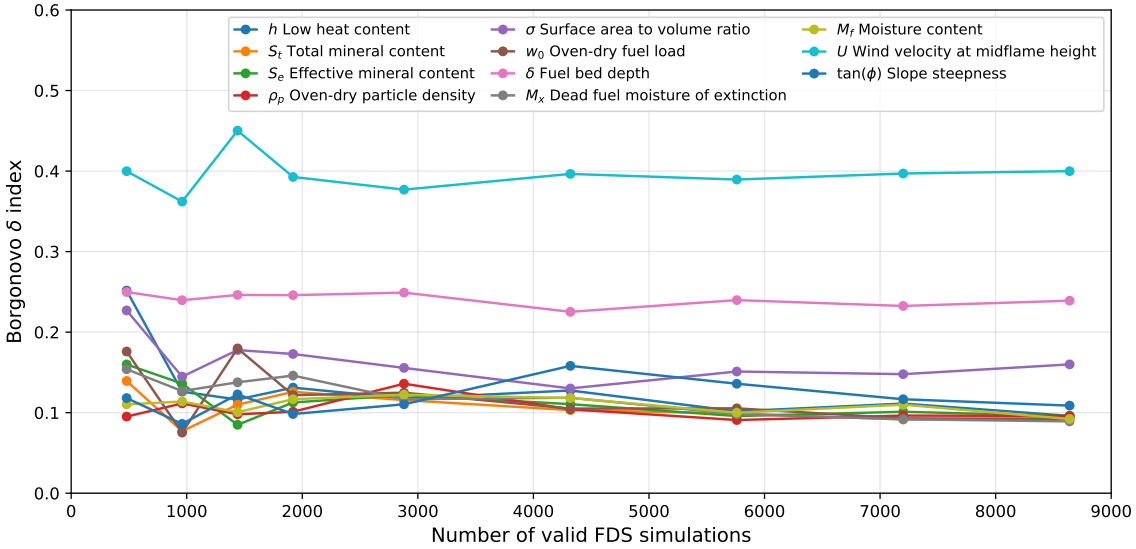


Figure 6: Convergence of Delta indices for LS4 using average spread speed as the output metric.

alter the dominant parameter hierarchy under the investigated conditions. Instead, the relative influence of secondary parameters changes between the formulations, while wind remains the dominant parameter.

6.5 Discussion

6.5.1 Interpretation and Transferability of Sensitivities

The direct evaluation and CFD-based sensitivity analyses consistently identify wind velocity at midflame height (U) as the dominant driver of wildfire spread. Fuel bed depth (δ) and the surface-area-to-volume ratio (σ) form a second sensitivity tier, while all remaining parameters exhibit substantially smaller contributions. The agreement between Borgonovo's Delta index and Sobol total-effect indices further demonstrates that this ranking is robust with respect to the selected global sensitivity measure and is therefore unlikely to be an artifact of a particular analysis technique.

These findings are consistent with previous global sensitivity studies of wildfire spread models. Earlier investigations based on the Rothermel formulation also identified wind speed and fuel characteristics as the dominant controls governing predicted fire spread, despite employing different sensitivity methods and sampling strategies (Salvador et al., 2001; Liu et al., 2015a; KC et al., 2021). Similarly, uncertainty analyses of the Rothermel model have repeatedly shown that variations in wind-related inputs produce substantially larger changes in predicted spread rates than most fuel-property parameters (Ervilha et al., 2017). The present study therefore confirms earlier observations while extending them through the combined application of Delta and Sobol sensitivity measures.

An important contribution of this work is the direct comparison between semi-empirical and physics-based wildfire models. Previous studies have investigated uncertainty propagation either within directly evaluated fire spread models or within CFD simulations separately (Valero et al., 2021). Here, identical parameter combinations are transferred from the Rothermel-Albini formulation to FDS, allowing the resulting sensitivity structures to be compared directly.

Importantly, the transferability of the sensitivity structure does not imply agreement in the absolute model responses. As shown in Figure 2, the direct evaluation of the semi-empirical Rothermel-Albini model produces a broader distribution of spread rates, particularly towards high values, than the forward spread speeds obtained from the FDS simulations. Thus, similar

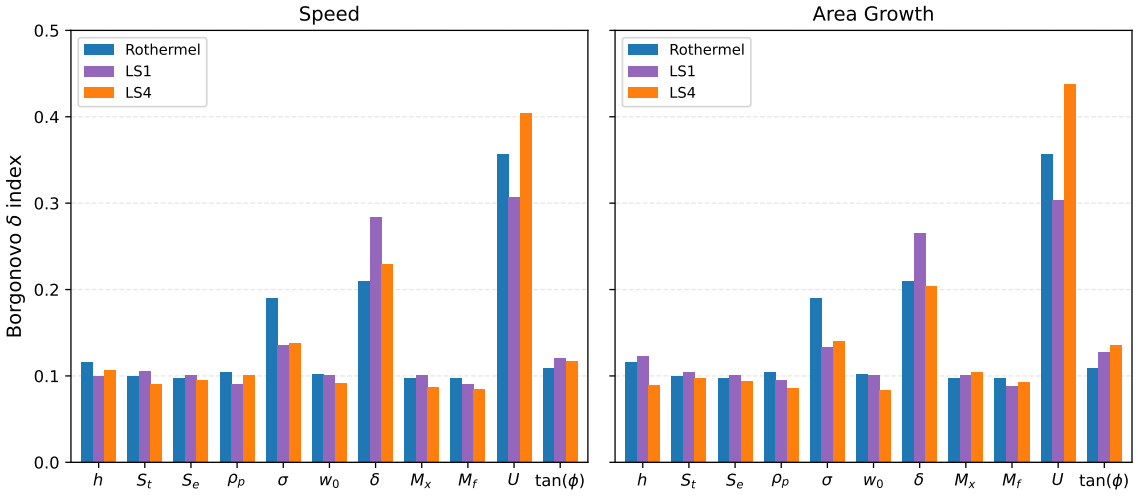


Figure 7: Delta index comparison for the 1-hour fuel class. The left panel compares the Rothermel rate of spread R with the FDS average spread speed along x for LS1 and LS4. The right panel compares the same semi-empirical reference with the FDS mean burned-area growth rate for LS1 and LS4, evaluated between the times at which 5% and 95% of the final burned area are reached.

parameter rankings can emerge even when the magnitude and distribution of the predicted fire-spread response differ between modeling approaches. The present results therefore support the transferability of relative parameter importance rather than equivalence of the predicted spread rates.

Wind velocity remains the primary driver in both modeling approaches, indicating that the dominant physical controls governing wildfire spread are preserved across increasing levels of model fidelity. This suggests that directly evaluated sensitivity analyses provide a reliable first-order approximation of parameter importance before computationally expensive CFD studies based on similar semi-empirical spread formulations are performed.

Although the dominant ranking is preserved, the FDS simulations modify the relative importance of several secondary parameters. Fuel-bed depth becomes more influential, whereas the contribution of the surface-area-to-volume ratio decreases compared with the Rothermel formulation. These differences may reflect the additional pathways through which input parameters affect fire propagation in the CFD framework. In addition to their direct influence on the Rothermel-based spread-rate calculation, individual parameters can affect combustion, heat release, and the resolved three-dimensional flow field, which in turn influence subsequent fire-front propagation. Consequently, the resulting sensitivities may represent the combined effects of several coupled mechanisms rather than the direct influence of the spread-rate formulation alone.

Terrain slope provides a particularly relevant example, as it enters the Rothermel-based spread-rate formulation directly while the inclined computational domain additionally modifies the resolved flow field. Its sensitivity in the coupled FDS simulations may therefore reflect both direct and flow-mediated effects.

6.5.2 Influence of Physical Coupling

A central objective of this study was to determine whether increasing physical coupling changes the sensitivity structure of wildfire spread models. This question can be addressed directly through the comparison of the two FDS level-set formulations.

LS1 represents a kinematic fire-spread model in which the level-set front propagates according

to the Rothermel spread-rate formulation while neglecting combustion feedback and fire-induced flow. Consequently, its sensitivity structure remains comparatively close to that of the direct evaluation. Wind velocity and fuel bed depth dominate the response, while the remaining parameters retain similar relative importance.

LS4 introduces substantially stronger coupling by resolving combustion, heat release, buoyancy-driven flow, and their interaction with the propagating fire front. Under these conditions, wind velocity becomes even more dominant, particularly when burned area growth is considered as response variable. At the same time, the influence of several secondary fuel parameters decreases slightly, indicating that additional physical interactions concentrate the overall model response more strongly on the dominant atmospheric forcing.

These observations suggest that increasing model complexity does not fundamentally alter which parameters govern wildfire spread. Instead, physical coupling primarily redistributes the relative importance of secondary parameters while reinforcing the dominant influence of wind. This finding is consistent with previous studies showing that higher-fidelity wildfire simulations preserve the primary spread mechanisms predicted by semi-empirical models while introducing additional interactions through combustion and flow coupling (Lautenberger, 2013; Vanella et al., 2021; Valero et al., 2021).

From a practical perspective, this result is encouraging because it indicates that directly evaluated sensitivity analyses remain informative even when the final application relies on fully coupled CFD simulations. At the same time, the differences observed between LS1 and LS4 demonstrate that simplified level-set formulations cannot fully reproduce the redistribution of sensitivities caused by additional physical processes.

6.5.3 Limitations

Several limitations should be considered when interpreting the present results.

First, the analysis is restricted to the 1-hour dead fuel class. Exploratory simulations for 10-hour and 100-hour fuels frequently failed to produce sustained fire spread within a short simulation time. Consequently, only the 1-hour fuel class provided a sufficiently large number of successful simulations for statistically meaningful sensitivity analyses. Future studies should investigate longer simulation times and alternative benchmark scenarios to extend the comparison to additional fuel classes.

Second, the CFD simulations are based on the CSIRO F19 benchmark configuration. Wind direction remains aligned with the positive x-axis, terrain slopes are limited to 15°, and a uniform mesh resolution of 5 m is employed throughout the study. These assumptions enable a controlled comparison between semi-empirical and CFD models but do not represent the full complexity of real wildfire environments, where heterogeneous fuels, variable wind fields, and complex terrain may introduce additional interactions.

A further limitation concerns the representation of terrain slope. In the Rothermel formulation, slope contributes through an empirical correction factor. Within FDS, however, slope is additionally represented geometrically by the inclined terrain surface. Consequently, terrain may influence fire spread through both the semi-empirical spread-rate formulation and the resolved three-dimensional flow field. Recent work has suggested that this dual representation may lead to an overestimation of slope effects under certain conditions (Pallikarakis and Kolaitis, 2026). Although the present results show only moderate sensitivity to terrain, dedicated studies are required to separate these mechanisms. The moderate sensitivity to terrain slope observed in the present study should likewise be interpreted within the investigated parameter range, as a broader or differently distributed range of slope conditions may alter its relative importance.

The global sensitivity analysis furthermore assumes statistically independent input parameters sampled from uniform probability distributions. In practical wildfire scenarios, however, several environmental variables exhibit significant statistical dependence. For example, periods of high wind speed are frequently associated with reduced fuel moisture or prolonged drought

conditions. Such dependencies may modify the effective parameter importance and cannot be captured by conventional variance- or density-based sensitivity measures. Extensions based on Shapley effects or other dependence-aware sensitivity measures therefore represent a promising direction for future research (Song, Nelson and Staum, 2016; Plischke, Rabitti and Borgonovo, 2021).

The sensitivity estimates are conditional on the prescribed input ranges and independent uniform input distributions and should not be interpreted as universal parameter rankings. Furthermore, the FDS sensitivity analysis was restricted to simulations with valid response metrics. If missing responses are associated with particular regions of the input parameter space, their exclusion may influence the estimated sensitivities. The FDS convergence assessment used nested subsets of a single sampling sequence rather than independently generated replicate samples. Therefore, it provides evidence of empirical index stability with increasing sample size but does not quantify variability across independent sampling realizations. These limitations are particularly relevant when interpreting small differences between secondary parameter sensitivities.

Finally, approximately two percent of the FDS simulations terminated prematurely because certain parameter combinations produced non-physical spread-rate conditions during the initialization of the level-set model. Although these failures had only a negligible influence on the convergence behavior of the sensitivity indices, they illustrate numerical limitations of the current implementation that demands further investigation.

6.5.4 Implications and Future Research

The present results have implications for both wildfire modeling and the application of global sensitivity analysis.

For semi-empirical fire spread models, the close agreement between Borgonovo's Delta index and Sobol total-effect indices demonstrates that robust parameter rankings can be obtained using complementary sensitivity measures. The dominant influence of wind velocity, followed by fuel bed depth and surface-area-to-volume ratio, is consistently reproduced regardless of the selected sensitivity metric and modeling approach.

More importantly, for the selected input parameters and their investigated ranges, the comparison with FDS shows that the dominant sensitivities remain largely transferable to the physics-based CFD framework. This suggests that computationally efficient sensitivity analyses based on the Rothermel formulation can provide valuable guidance for parameter screening, uncertainty prioritization, and experimental design before performing large-scale CFD investigations with related spread formulations. However, this transferability should be interpreted within the investigated parameter space and model configuration and should not be assumed to extend directly to substantially different fuel types, parameter ranges, or fire-spread formulations.

The comparison between LS1 and LS4 further demonstrates that increasing physical realism primarily redistributes the influence of secondary parameters rather than changing the dominant controls governing wildfire spread. Consequently, the choice of level-set formulation becomes particularly important when detailed parameter rankings or calibration studies are performed, even if the dominant spread mechanisms remain unchanged.

Future work should extend the analysis towards more realistic wildfire scenarios, including heterogeneous fuels, complex terrain, dynamically varying wind conditions, and longer simulation periods. In addition, sensitivity analyses that explicitly account for dependent input variables should be investigated using dependence-aware methods such as Shapley effects. Finally, the transferability of sensitivity structures should be examined for additional wildfire models and benchmark experiments to assess whether the observations reported here generalize beyond the CSIRO F19 configuration.

References

Abatzoglou, J.T., Kolden, C.A., Cullen, A.C., Sadegh, M., Williams, E.L., Turco, M., Jones, M.W., 2025. Climate change has increased the odds of extreme regional forest fire years globally. Nature Communications 16, 6390. doi:10.1038/s41467-025-61608-1.

Andrews, P.L., 2018. The Rothermel Surface Fire Spread Model and Associated Developments: A Comprehensive Explanation. General Technical Report RMRS-GTR-371. U.S. Department of Agriculture, Forest Service, Rocky Mountain Research Station. Fort Collins, CO. doi:10.2737/RMRS-GTR-371.

Balbi, J.H., Morandini, F., Silvani, X., Filippi, J.B., Rinieri, F., 2009. A physical model for wildland fires. Combustion and Flame 156, 2217–2230. doi:10.1016/j.combustflame.2009.07.010.

Borgonovo, E., 2007. A new uncertainty importance measure. Reliability Engineering & System Safety 92, 771–784. doi:10.1016/j.ress.2006.04.015.

Brohus, H., Nielsen, P.V., Petersen, A.J., Sommerlund-Larsen, K., 2007. Sensitivity analysis of fire dynamics simulation, in: Proceedings of Roomvent 2007: Helsinki 13–15 June 2007, FINVAC ry.

Brännström, F., Jamil, H., Nouroozyan, M., Sailer, J., 2025. Challenges in fire spread modeling—from bench scale up to wildfire scale, in: Bracke, S., Pieper, R. (Eds.), Safety Engineering: Fundamentals, Methods, Research Topics. Springer Fachmedien Wiesbaden, Wiesbaden, pp. 299–319. doi:10.1007/978-3-658-47473-7_13.

Cheney, N.P., Gould, J.S., Catchpole, W.R., 1993. The influence of fuel, weather and fire shape variables on fire-spread in grasslands. International Journal of Wildland Fire 3, 31–44. doi:10.1071/WF9930031.

Cheney, N.P., Gould, J.S., Catchpole, W.R., 1998. Prediction of fire spread in grasslands. International Journal of Wildland Fire 8, 1–13. doi:10.1071/WF9980001.

Ervilha, A.R., Pereira, J.M.C., Pereira, J.C.F., 2017. On the parametric uncertainty quantification of the Rothermel's rate of spread model. Applied Mathematical Modelling 41, 37–53. doi:10.1016/j.apm.2016.06.026.

Herman, J., Usher, W., 2017. SALib: An open-source python library for sensitivity analysis. Journal of Open Source Software 2, 97. doi:10.21105/joss.00097.

Jolly, W.M., 2007. Sensitivity of a surface fire spread model and associated fire behaviour fuel models to changes in live fuel moisture. International Journal of Wildland Fire 16, 503–509. doi:10.1071/WF06077.

KC, U., Aryal, J., Garg, S., Hilton, J., 2021. Global sensitivity analysis for uncertainty quantification in fire spread models. Environmental Modelling & Software 143, 105110. doi:10.1016/j.envsoft.2021.105110.

Kelsey, A., Gant, S., McNally, K., Betteridge, S., 2014. Application of global sensitivity analysis to FDS simulations of large LNG fire plumes, in: Hazards 24, pp. 283–293.

Lautenberger, C., 2013. Wildland fire modeling with an eulerian level set method and automated calibration. Fire Safety Journal 62, 289–298. doi:10.1016/j.firesaf.2013.08.014.

Liu, X.p., Tong, Z.j., Zhang, J.q., Song, C.t., 2023. Uncertainty simulation of large-scale discrete grassland fire spread based on Monte Carlo. Fire Safety Journal 135, 103713. doi:10.1016/j.firesaf.2022.103713.

Liu, Y., Hussaini, M.Y., Ökten, G., 2015a. Global sensitivity analysis for the Rothermel model based on high-dimensional model representation. Canadian Journal of Forest Research 45, 1474–1479. doi:10.1139/cjfr-2015-0148.

Liu, Y., Jimenez, E., Hussaini, M.Y., Ökten, G., Goodrick, S., 2015b. Parametric uncertainty quantification in the Rothermel model with randomised quasi-Monte Carlo methods. International Journal of Wildland Fire 24, 307–316. doi:10.1071/WF13097.

Mallet, V., Keyes, D.E., Fendell, F.E., 2009. Modeling wildland fire propagation with level set methods. Computers & Mathematics with Applications 57, 1089–1101. doi:10.1016/j.camwa.2008.10.089.

McGrattan, K., Hostikka, S., Floyd, J., McDermott, R., Vanella, M., Mueller, E., Paul, C., 2013a. Fire Dynamics Simulator Technical Reference Guide: Volume 3: Validation. NIST Special Publication 1018-3. National Institute of Standards and Technology. Gaithersburg, MD. doi:10.6028/NIST.SP.1018.

McGrattan, K., Hostikka, S., Floyd, J., McDermott, R., Vanella, M., Mueller, E., Paul, C., 2013b. Fire Dynamics Simulator User's Guide. Technical Report NIST Special Publication 1019. National Institute of Standards and Technology. Gaithersburg, MD. doi:10.6028/NIST.SP.1019.

Moore, P.F., 2019. Global wildland fire management research needs. Current Forestry Reports 5, 210–225. doi:10.1007/s40725-019-00099-y.

Pallikarakis, C.N., Kolaitis, D.I., 2026. Comparative assessment of wildland fire rate of spread models: Influence of terrain slope. Fire Safety Journal 162, 104774. doi:10.1016/j.firesaf.2026.104774.

Plischke, E., Rabitti, G., Borgonovo, E., 2021. Computing shapley effects for sensitivity analysis. SIAM/ASA Journal on Uncertainty Quantification 9, 1411–1437.

Purnomo, D.M.J., Zamanialaei, M., Earle, M., Theodori, M., Qin, Y., Lautenberger, C., Trouvé, A., Gollner, M., 2026. Sensitivity of ELMFIRE to real-world input datasets for WUI fire modeling. Fire Safety Journal 161, 104651. doi:10.1016/j.firesaf.2026.104651.

Quaresma, T.L.S., Hehnen, T., Arnold, L., 2024. Sensitivity analysis for an effective transfer of estimated material properties from cone calorimeter to horizontal flame spread simulations. Fire Safety Journal 144, 104116. doi:10.1016/j.firesaf.2024.104116.

Rothermel, R.C., 1972. A Mathematical Model for Predicting Fire Spread in Wildland Fuels. Research Paper INT-RP-115. U.S. Department of Agriculture, Forest Service, Intermountain Forest and Range Experiment Station. Ogden, UT. doi:10.2737/INT-RP-115.

Saltelli, A., 2002. Making best use of model evaluations to compute sensitivity indices. Computer Physics Communications 145, 280–297. doi:10.1016/S0010-4655(02)00280-1.

Salvador, R., Piñol, J., Tarantola, A., Pla, E., 2001. Global sensitivity analysis and scale effects of a fire propagation model used over mediterranean shrublands. Ecological Modelling 136, 175–189. doi:10.1016/S0304-3800(00)00419-1.

Song, E., Nelson, B.L., Staum, J., 2016. Shapley effects for global sensitivity analysis: Theory and computation. SIAM/ASA Journal on Uncertainty Quantification 4, 1060–1083. doi:10.1137/15M1048070.

United Nations Committee of Experts on Global Geospatial Information Management, 2026. Wildfire response, community protection and resilience.

Valero, M.M., Jofre, L., Torres, R., 2021. Multifidelity prediction in wildfire spread simulation: Modeling, uncertainty quantification and sensitivity analysis. Environmental Modelling & Software 141, 105050. doi:10.1016/j.envsoft.2021.105050.

Vanella, M., McGrattan, K., McDermott, R., Forney, G., Mell, W., Gissi, E., Fiorucci, P., 2021. A multi-fidelity framework for wildland fire behavior simulations over complex terrain. Atmosphere 12, 273. doi:10.3390/atmos12020273.