

Enhancing Wildfire Propagation Model Predictions Using UAV Swarm-Based Real-Time Wind Measurements: A Conceptual Framework

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ABSTRACT

The dynamic behaviour of wildfires is mainly influenced by weather, fuel, and topography. Based on fundamental conservation laws involving numerous physical processes and large scales, atmospheric models require substantial computational resources. Therefore, coupling wildfire and atmospheric models is impractical for high resolutions, even for small scales. Instead, a static atmospheric wind field is typically input into the wildfire model, either as boundary conditions on the control surface or distributed throughout the control volume. Wildfire propagation models may be (i) *data-driven*; (ii) *theoretical*; or (iii) *mechanistic surrogates*. Data-driven models are beyond the scope of this paper. Theoretical models are based on conservation laws (species, energy, mass, momentum) and therefore are computationally expensive—e.g. the Fire Dynamics Simulator (FDS). Mechanistic surrogate models do not closely follow fire dynamics laws but a different set of somewhat related laws observed to make predictions more efficiently and with sufficient accuracy—e.g. FARSITE and the Level-Set FDS (LS-FDS). Whether theoretical or mechanistic surrogate, these wildfire models may be coupled with or decoupled from wind models (e.g. the Navier-Stokes equations). Only coupled models account for the effect of the fire on the wind field. In this paper, a series of simulations of wildfire propagation on grassland are performed using LS-FDS to study the impact of the fire-induced wind on the fire propagation dynamics. Simulations of coupled and decoupled models are compared for different terrain slopes and atmospheric wind velocities. Results indicate that different coupling strategies can lead to the Rate of Spread (RoS) differing by as much as 23% for 30% up-slope terrains. Aiming to capture the fire-wind interaction without the hefty cost of solving the Navier-Stokes equations, a conceptual framework is proposed: 1) a swarm of UAVs measure wind velocities at a certain altitude; 2) the wind field is constructed with the acquired data; and 3) the wind field is downscaled and fed into the wildfire model periodically. As proof of concept, a series of simulations are performed using an in-house decoupled physics-based reduced-order fire propagation model (FireProM-F) enhanced by wind field "measurements". In this paper, wind velocities are not actually measured but extracted from high-fidelity physics-based Large Eddy Simulations within FDS (taken as ground truth). As expected, higher measurement frequencies lead to more accurate predictions of the RoS, and to more realistic formations of the propagating fire front. Finally, an initial attempt is made at studying the effect of wind measurement uncertainty on the model predictions by adding Gaussian noise. Preliminary results show that higher noise leads to marginally slower propagation of the fire front.

1. Introduction

The occurrence and behaviour of wildfires are greatly influenced by a combination of interrelated factors such as the ignition source, fuel composition and distribution, weather, and topography [1]. Wind—specifically, ground-level wind—is the most widely studied parameter involved in the fire-atmosphere interaction [2]. According to Gisborne [3], surface wind affects fire behaviour via four main mechanisms: (i) varying fuel moisture by carrying dry or humid air; (ii) varying the Rate of spread (RoS) of the fire; (iii) carrying ignited branches or embers to unburned areas

thus causing the ignition of spot fires; and (iv) bringing oxygen flux to the fire flame thus boosting combustion.

Sullivan [4, 5, 6] classifies wildfire propagation models into three types: (i) *physical and quasi-physical* models, which are based on fundamental physics or chemistry of combustion [4]; (ii) *empirical and quasi-empirical* models, which are based on the statistical analysis of obtained data [5]; and (iii) *mathematical analogues and simulation* models, which are based on some mathematical conceit that coincidentally simulates the spread of fire [6]. Innocente and Grasso [7, 8] classify them into three types (see Figure 1, yellow boxes): (i) *theoretical* models, which are physics-based and involve conservation laws; (ii) *data-driven* models, which are constructed or fitted using actual or synthetic data; and (iii) *mechanistic surrogate* models, which make use of mechanisms not directly related to fire dynamics. In turn, Bakhshaii and Johnson [9] classify wildfire propagation models into three categories based on the level of their interaction with wind models: (i) *non-coupled*; (ii) *semi-coupled*; and (iii) *fully-coupled*. A wildfire model in which fire and wind models interact locally without being

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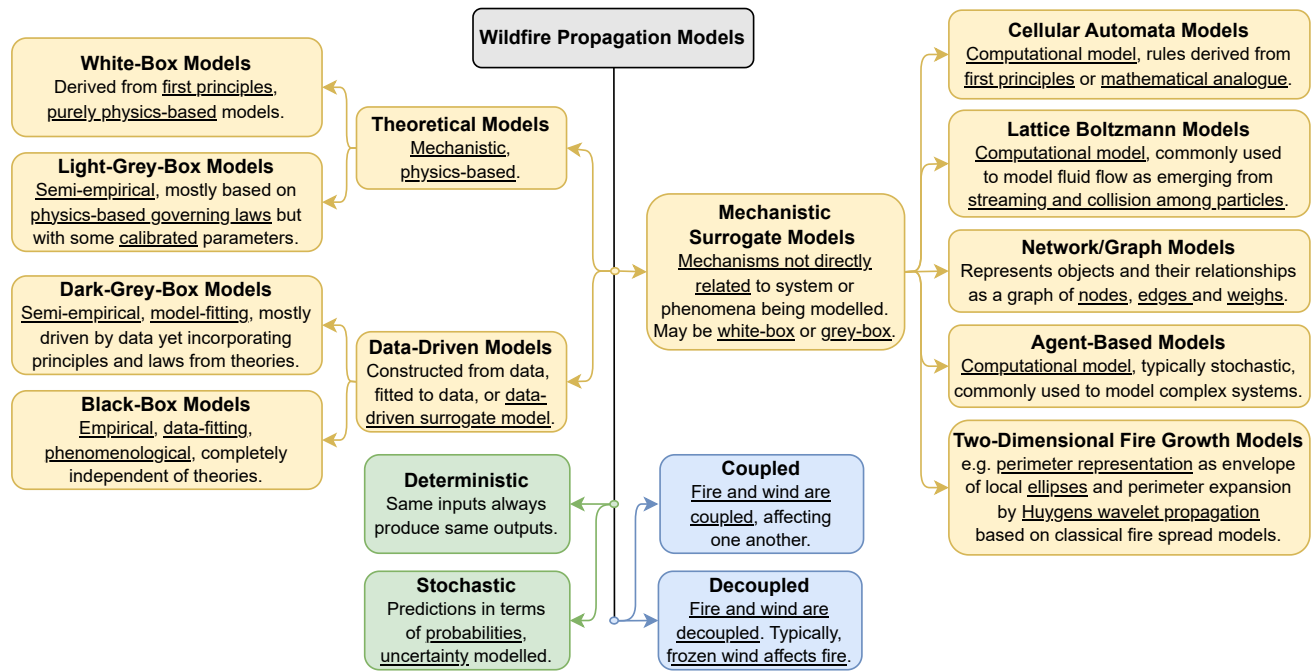


Figure 1: Classification of fire propagation models. Modified from [7] to make it specific to wildfires, and to explicitly differentiate coupled form decoupled models.

coupled with an atmospheric model would fall under the *semi-coupled* category. In this paper, we classify wildfire models into (i) *coupled* and (ii) *decoupled* depending on whether fire and wind models interact (see Figure 1, blue boxes). This refers to the wildfire model alone, irrespective of whether it is coupled with an atmospheric model.

Seeking computational efficiency for operational use, some models such as FARSITE [10] and FireProM-F [8] are *decoupled* from wind models, thus neglecting the impact of the fire on the wind field. This increases the epistemic uncertainty. FARSITE is a *mechanistic surrogate* model, which mainly relies on a simplified analytical calculation of the RoS and on Huygens' principle to approximate the propagation of the fire perimeter as if it were a wave front. FireProM-F [8, 11] is a *theoretical* reduced-order model based on energy and species conservation laws with some calibrated physically-meaningful parameters (*light-grey-box* model). Despite being physics-based, it may run faster-than-real-time under certain circumstances (scenarios, settings, computing power), although this comes at the expense of being decoupled from wind models and therefore using a frozen wind field. While *decoupled* models may provide fast simulations of wildfire propagation [9], they are unable to capture structures such as plume-driven fire, whirls, or horizontal roll vortices [12].

Conversely, *coupled* models such as the Fire Dynamics Simulator (FDS) [13] and FIRETEC [14] try to solve the fluid dynamics and thermo-chemical equations simultaneously in order to capture the dynamics of a wildfire [9]. Even though some of these models (e.g. WRF-FIRE [15]) could potentially provide faster-than-real-time simulations

under specific configurations and using high-performance facilities, an accurate numerical solution over a large domain is prohibitively computationally expensive [9]. This restricts the practical use of this type of models.

Even though the fire-wind coupling strategy significantly affects the simulation results, this is rarely studied systematically in the literature. Lopes et al. [16] studied the effects of the mesh size and of the wind update criterion on the fire propagation dynamics. They found that the mesh size has a high impact on the RoS and propagation dynamics of the fire, though this impact becomes less noticeable as the mesh size decreases. Nevertheless, a truly mesh-independent simulation is unlikely to be achieved. In turn, comparing the results of a series of coupled and decoupled wildfire simulations, they observed that coupled ones predict significantly smaller burned areas. Interestingly, it was also found that reducing the wind field update interval to once every five time-steps does not lead to significant variation in results, yet it notably reduces the computational effort [16]. Recently, Tavakol Sadrabadi et al. [17] also found that the burned area and the RoS are smaller for coupled simulations.

Thus, the choice of the right wildfire propagation model is highly dependent on the intended application: *coupled* models are more rigorous though computationally expensive (hence with limited operational use) whereas *decoupled* models decrease the computational cost at the expense of disregarding the effect of the fire on the wind field (hence sacrificing prediction accuracy). In order to compensate for this drawback, efforts have been made to increase the accuracy of the wind estimations; e.g. using Numerical Weather Prediction (NWP) models together with methods

to downscale and refine these estimations over the terrain of interest [18]. However, these large-scale models cannot capture wildfires local effects.

During the past few years, unmanned aerial vehicles (UAVs) have gained popularity in various industries and applications. They offer a low-cost option for firefighting, prevention, detection, and real-time assistance using either a single UAV or a collection of them [19, 7]. Usually, UAVs (a.k.a. drones) are fitted with sensors that allow them to communicate with each other and to provide data to the ground station—e.g. GPS for navigation purposes [19], infrared and digital cameras for surveying and fire detection [20], and measuring sensors for aerosol concentrations [21] and wind velocities [21, 22, 23, 24]. Firefighting activities largely depend on receiving accurate real-time data such as fire propagation characteristics, fuel distribution, and wind patterns. The availability of such data significantly increases the probability of success of the whole operation [25]. The use of drones in wildfire management has grown steadily in recent times, with most research focused on fire detection [26], monitoring [27], and suppression [28, 7, 29]. However, these drones could also be equipped with sensors to measure wind velocities while performing other tasks like fire monitoring and/or suppression. Therefore, this paper proposes a novel conceptual framework for improving the accuracy of *decoupled* wildfire propagation models using real-time wind field measurements carried out by a swarm of UAVs. As a proof of concept, these "*measurements*" are not actually taken by drones in the simulations performed in this paper but extracted from high-fidelity physics-based simulations viewed as ground truth. The proposed framework is mainly aimed at increasing the prediction accuracy of decoupled wildfire propagation models which disregard the effect of the fire on the wind field. However, it would also make it possible to capture variable atmospheric winds on site without resorting to atmospheric models.

The remainder of this paper is organised as follows: Section 2 provides a brief overview of the main fire propagation models used in this research, namely FDS and its sub-models (Lagrangian Particle, Boundary Fuel, and Level Set), and FireProM-F; Section 3 discusses coupling strategies for fire-wind models and studies their impact on the RoS and fire propagation dynamics under different slopes and wind conditions using LS-FDS; Section 4 introduces the proposed method to improve the accuracy of decoupled wildfire propagation model predictions using real-time wind measurements carried out by a swarm of UAVs; whilst Section 5 presents the results obtained from simulations using FireProM-F with and without noise in the wind measurements; finally, Section 6 provides a summary of the research findings and derived conclusions.

2. Fire Propagation Models

This section presents a brief overview of the fire propagation models used for the simulations in this paper.

2.1. Fire Dynamics Simulator

With a focus on smoke and heat transfer from fires, the Fire Dynamics Simulator (FDS) numerically solves a variant of the Navier-Stokes equations suitable for low-speed, thermally-driven flow. The main algorithm includes an explicit predictor-corrector method that is second-order accurate in space and time. Turbulence is modelled via Large Eddy Simulations (LES). A Direct Numerical Simulation (DNS) could be carried out instead, should the mesh be sufficiently fine. FDS employs a one-step, mixing-controlled chemical reaction with three bundled species for most applications: *products*, *fuel*, and *air*. Reactions that are not necessarily mixing-controlled and multiple reactions could also be considered under certain conditions. To approximate the governing equations and discretise the domain, a Cartesian grid is used [30]. FDS offers various models for the simulation of wildfire spread based on the desired level of physics required and the available computing resources: the Lagrangian Particle Model (LPM), the Boundary Fuel Model (BFM), and the Level-Set (LS) model.

2.1.1. Lagrangian Particle Model

In this model, vegetation is represented by a collection of Lagrangian particles heated via convection-radiation heat transfer. These particles could be used to represent leaves, grass, trees, etc. With sufficient grid refinement, LPM can be used for simulation of the front, back, and flank fire across surface as well as high-level vegetations (e.g. trees) [31].

2.1.2. Boundary Fuel Model

This model is an option when a coarse grid is desired to discretise a thin vegetation layer. In this case, the vegetation is modelled as a porous boundary consisting of a layer of dry vegetation, air and moisture. The height of the vegetation is unresolved on the grid, and may be used for grid sizes of up to 10 m [30, 31].

2.1.3. Level Set Model

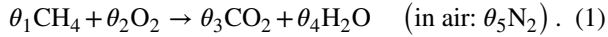
This model is used for wildfires propagating across large areas which cannot be discretised with a grid sufficiently fine for physics-based models. It is based on the assumption that, under specific wind, slope, and vegetation circumstances, a surface fire will spread from a single location with an ellipse-shaped fire perimeter that has a constant length-to-breadth ratio for the effective wind vector. The LSM uses the Rothermel-Albini's surface fire spread formula and Albini's 13 fuel models [30]. It may be used in four different modes:

- **MODE 1:** Wind field is uniform and unaffected by terrain or fire (frozen uniform wind field). Only fire model runs. *Decoupled* wildfire model in Figure 1.
- **MODE 2:** Wind field affected by terrain but unaffected by fire (frozen non-uniform wind field once fire ignites). Fire affected by frozen wind. *Decoupled* wildfire model in Figure 1.
- **MODE 3:** Wind field follows terrain but there is no actual fire in the simulation (just front-tracking). [30]

- MODE 4: Wind field affected by terrain and fire. Fire affected by wind. *Coupled* wildfire model in Figure 1.

2.2. Fast Fire Propagation Model

The Fast Fire Propagation Model (FireProM-F) [8] is a physics-based model developed with computational efficiency in mind, aiming for faster-than-real-time (FtRT) simulations. It is governed by a two-dimensional (2D) reaction-diffusion equation that describes the combustion of a vegetation stratum represented by a mono-phase medium composed of pre-mixed gas of fuel and air. The latter is assumed to be composed of oxygen, carbon dioxide, water vapour, and nitrogen. The reference chemical reaction (assumed to be irreversible) is the combustion of methane in air:



The model is formulated as a system of five partial differential equations (PDEs), where Equation (2) represents the conservation of energy whilst the four equations in (3) represent the conservation of chemical species.

$$\rho \frac{\partial}{\partial t} (c_p T) = R_c - \nabla \cdot (\mathbf{q}_c + \mathbf{q}_d + \mathbf{q}_r) + Q_{cz} + Q_{rz} + Q_w \quad (2)$$

$$\frac{\partial X_i}{\partial t} = -\frac{\theta_i}{\theta_{\text{fuel}}} \frac{M_i}{M_{\text{fuel}}} r; \quad \text{with } i = 1, 2, 3, 4, \quad (3)$$

where:

- R_c : combustion energy source;
- $\mathbf{q}_c$: conductive heat flux;
- $\mathbf{q}_d$: interdiffusional enthalpy flux;
- $\mathbf{q}_r$: 2D radiation heat flux;
- Q_{cz} : vertical convection heat loss;
- Q_{rz} : vertical radiation heat loss.
- Q_w : transport term due to wind;
- X_i : mass fraction of i^{th} chemical species.
- M_i : molar mass of i^{th} chemical species.
- r : combustion rate.

With this dimensionality reduction, some fire dynamics phenomena like buoyancy are disregarded, though vertical convection (Q_{cz}) and vertical radiation (Q_{rz}) terms are added to the conservation of energy equation. FireProM-F does not account for the conservation of mass or momentum, hence neglecting the effect of the fire on the wind field. The diffusion coefficient is augmented (via calibration) to somewhat compensate for this.

The system is closed with the equations for the molar mass of the mixture, the heat capacity of the mixture, the combustion rate (modelled by the Arrhenius law), and the combustion enthalpy. Refer to [8] for more details.

The transport term due to wind (Q_w) in Equation (2) is calculated as in Equation (4):

$$Q_w = -\rho c_w \mathbf{u} \cdot \nabla (c_p T) \quad (4)$$

where $\mathbf{u} = (u_x, u_y)$ is the atmospheric wind velocity, c_w is the wind reduction coefficient (which may also be used as a calibration parameter), T is the temperature, c_p is the heat capacity coefficient at constant pressure, and ρ is the gas mixture density. This is solved using an upwind scheme.

The numerical scheme for the solution of Equations (2) and (3) is a finite difference method with a 2nd-order central difference for space and the 4th-order Runge-Kuta method for time discretisations. Refer to [8] for more details.

This reduced-order model is adopted in this paper as a fast (yet still physics-based) simulator to test the proposed framework. The latter aims to enhance the accuracy of the transport term (Q_w) by feeding the model with wind velocities ($\mathbf{u}$) measured by a swarm of UAVs. This would account for both a variable atmospheric wind and the effect of the fire on the wind field.

2.3. Calibration and Validation

2.3.1. Experimental Data

Numerical simulations are validated against the flat terrain grassland fire spread experiments carried out by the Commonwealth Scientific and Industrial Research Organisation (CSIRO) [32]. The selected experiments are the C064 and F19. These were performed in the middle of the dry season on flatlands of $100 \times 100 \text{ m}^2$ covered with dry Kerosene grass and of $200 \times 200 \text{ m}^2$ covered with dry Kangaroo grass, respectively. Measured properties in [32] and unmeasured properties assumed in [31] are shown in Table 1.

Most simulations are performed using LS-FDS to study the effect of coupling/decoupling fire-fuel models. Albini's *Fuel Model 1* (short grass) and *Fuel Model 3* (tall grass) are used for the simulated C064 and F19 experiments, respectively [30]. Some modifications are performed to resolve mismatches between the characteristics of the fuel models in [30] and actual experimental measurements.

2.3.2. Boundary Conditions and Grid Sensitivity

Open boundary conditions are used at the top, outlet, right, and left boundaries. The ambient wind is simulated within the domain using the Monin-Obukhov similarity theory, with Obukhov length scale $L = -500$, aerodynamic roughness height $z_0 = 0.03$, and wind speed at a reference height of 2 m above ground level (AGL) $u_r = 4.6 \text{ m/s}$.

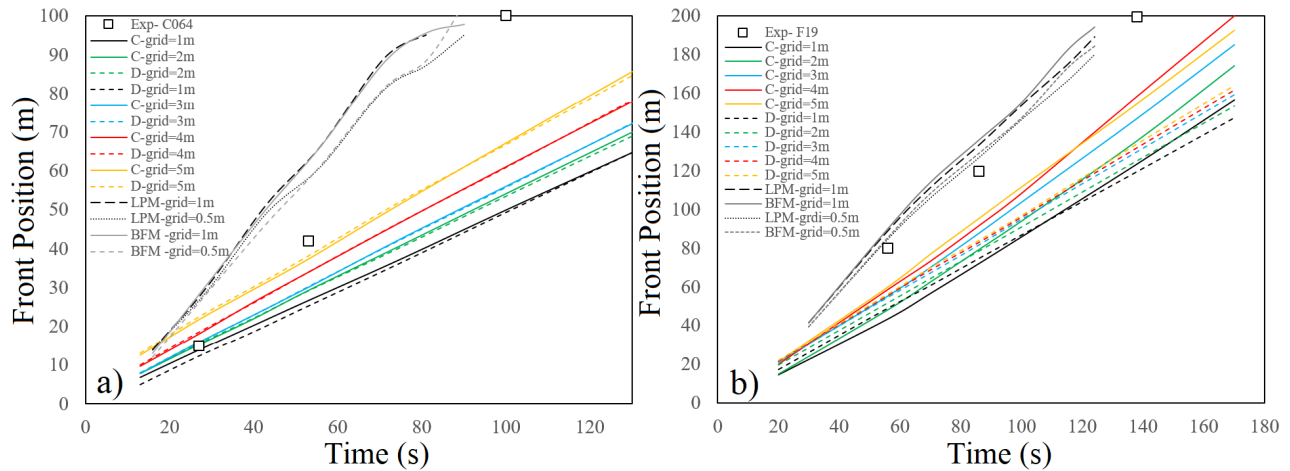
Structured Cartesian grids with equal spacing in x , y , z directions are used to discretise a $120 \times 120 \times 40 \text{ m}^3$ domain for the C064 experiments, and a $240 \times 240 \times 100 \text{ m}^3$ domain for the F19 experiments. In order to study the sensitivity of the simulated fire propagation to the grid cell size, sizes between $1 \times 1 \times 1 \text{ m}^3$ and $5 \times 5 \times 5 \text{ m}^3$ are tested using LS-FDS, and of sizes $0.5 \times 0.5 \times 0.5 \text{ m}^3$ and $1 \times 1 \times 1 \text{ m}^3$ using BFM-FDS and LPM-FDS.

The evolution of the fire front for different cell sizes is shown in Figure 2 for the (a) C064 and (b) F19 CSIRO experiments using the three FDS sub-models. In particular, LS-FDS is run using both the coupled and uncoupled strategies. As a general trend, it can be observed that increasing the

Table 1

Measured properties of CSIRO experiments [32] and utilized values for simulations based on [13, 31]

Property	Unit	Case C064	Case F19
Wind speed	m/s	4.6	4.8
Ambient Temperature	°C	32	34
Surface Area to Volume Ratio	m ⁻¹	9,770	12,240
Grass Height	m	0.21	0.51
Bulk Mass Per Unit Area	kg m ⁻²	0.283	0.313
Moisture Fraction	%	6.3	5.8
Measured RoS	m s ⁻¹	1.2	1.5
Fuel	-	Cellulose (C ₆ H ₁₀ O ₅)	Cellulose (C ₆ H ₁₀ O ₅)
Heat of Combustion	kJ kg ⁻¹	15,600	15,600
Soot Yield	kg kg ⁻¹	0.015	0.015
Char Yield	kg kg ⁻¹	0.2	0.2
Specific Heat	kJ kg ⁻¹ K ⁻¹	1.5	1.5
Conductivity	kJ kg ⁻¹ K ⁻¹	0.1	0.1
Density	kg m ⁻³	512	512
Heat of Pyrolysis	kJ kg ⁻¹	418	418
Pyrolysis Temperature	°C	200	200
Obukhov Length	m	-500	-500
Aerodynamic Roughness Length	m	0.03	0.03
Drag Coefficient	-	2.8	2.8
Soil Specific Heat	kJ kg ⁻¹ K ⁻¹	2.0	2.0
Soil Conductivity	W m ⁻¹ K ⁻¹	0.25	0.25
Soil Density	kg m ⁻³	1,300	1,300

**Figure 2:** Evolution of the fire front for different mesh sizes using LS-FDS with coupled (C) and decoupled (D) strategies, LPM-FDS, and BFM-FDS models for (a) C064 and (b) F19 CSIRO experiments.

mesh/cell size results in increasing the RoS of the fire, which is consistent with the results in [31].

2.3.3. Level-Set No-Wind No-Slope RoS Calibration

The analysis in Section 2.3.2 shows that the no-wind no-slope RoS (RoS_0) is sensitive to the refinement of the grid (i.e. to the mesh/cell size). Though less evident in the C064 experiments, it can also be observed in Figure 2 that coupled (C) wildfire models predict faster RoS (and closer to the experimental results) than the corresponding decoupled (D) ones. The remaining simulations in this paper are carried

out for the F19 experiment due to its larger area and longer duration, which results in more meaningful comparisons.

In order to calibrate the LS-FDS, the default values of the RoS_0 in Albini's fuel models are tuned so that the model outputs RoS values comparable to those obtained from the CSIRO experiments. Figure 3 shows the position and perimeter of the fire obtained for the simulated CSIRO F19 experiment using the coupled LS-FDS (MODE 4) with calibrated RoS_0 for 2 m, 3 m, and 5 m grid sizes at three different times from ignition. Results obtained using BFM-FDS and LPM-FDS are also included in the figure.

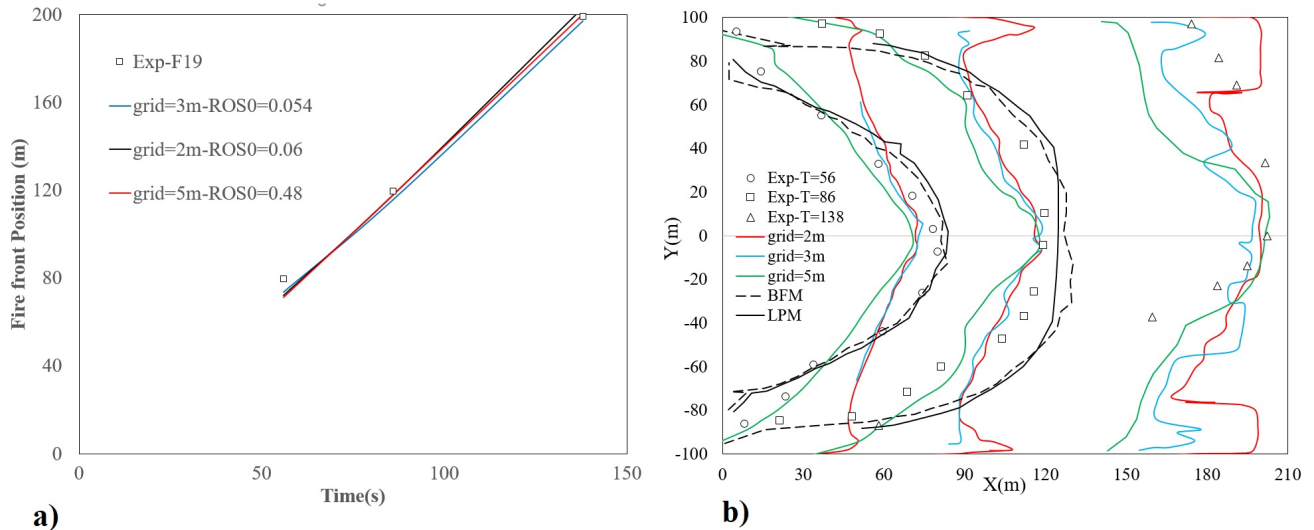


Figure 3: (a) Position and (b) perimeter of fire for CSIRO F19 experiment using BFM-FDS, LPM-FDS, and coupled LS-FDS with calibrated RoS_0 for three grid sizes at three different times after ignition. Experimental results also provided for reference.

3. Coupling Strategies for Fire-Wind Models

Figure 3 shows that the coupled LS-FDS with calibrated RoS_0 predicts the CSIRO F19 experiment accurately under no-slope condition. The effects of fire-wind coupling on the headfire position and the corresponding RoS for a range of wind speeds and topography slopes during up-slope propagation can be observed in Figure 4, where $2 \times 2 \times 1 \text{ m}^3$ cells are used for spatial discretisation. Given that FDS uses structured grids, a sloped topography is modelled using a staircase of cubic blocks.

Figure 4 shows (a) the headfire position (distance travelled) for eight different wind speeds and (b) their corresponding RoS for horizontal topography. It also shows (c) the headfire position and (d) their corresponding RoS for a fire propagating up slope for all nine possible combinations of three slopes (5 %, 15 %, 30%) and three wind speeds (1 m/s, 5 m/s, 10 m/s). Both coupled (C) and decoupled (D) LS-FDS are used in each case. Note that *wind speed* refers to atmospheric horizontal wind, whilst the resulting up-slope wind is always higher. As expected, higher wind speed and higher topography slope (for up-slope propagation) lead to higher RoS. Furthermore, higher wind speeds of up to 10 m/s and higher surface slopes of up to 30% also result in larger differences between predictions by corresponding coupled and decoupled fire-wind models (in agreement with experimental results [33]). For example, the difference between coupled and decoupled predictions of the RoS is 0.44 m/s for 30% slope and 5 m/s wind, whereas it is 1.51 m/s for 30% slope and 10 m/s. The RoS predicted by coupled LS-FDS appears to be generally higher than the one predicted by decoupled LS-FDS for wind speeds of up to 12 m/s. For horizontal topography in Figure 4 (b), this trend seems to invert for wind speeds approximately between 12 m/s and 20 m/s, with the coupling strategy making little to no

difference for a wind speed of 20 m/s. However, more data-points would be required to support this observation.

It is important to note that these simulations using LS-FDS seem to indicate that increasing wind speeds always leads to increasing RoS. However, experimental results [2, 34] showed that a turning point and a reduction of the RoS is to be expected. Since LS-FDS is not physics-based, it is reasonable to infer that it does not capture some of the relevant underlying fire propagation dynamics, and therefore may make unreliable predictions for higher wind speeds (in these experiments, higher than 12–13 m/s).

Wildfires can propagate up slope surprisingly fast due to the heating of unburned fuel ahead of the fire as the plume attaches to the slope surface; i.e. to the fuel bed [35]. The RoS increases with the increase in the length of the plume attachment, which grows as the angle between the fire plume and the fuel bed shrinks. This angle shrinks with increasing *flame tilt angle* (θ) and with increasing *fuel bed inclination angle* (α), where θ is defined as the angle between the centerline of the individually pioneering flame and the vertical axis [36]. In turn, θ increases with increasing uphill *wind speed* and with increasing α due to the resulting asymmetry of the *air entrainment*. Since the buoyancy force has an uphill component, the air entrainment into the fire from the burned side (upstream) is greater, tilting the plume towards the unburned downstream vegetation [37]. Therefore, higher uphill *wind speeds* and higher *surface slopes* lead to faster uphill fire propagation (higher RoS) due to the resulting larger *plume attachment length*. Under no ambient wind condition, the plume attachment length is more sensitive to fuel bed inclination angles higher than 15° , increasing dramatically for angles higher than 24° (the so-called *critical inclination angle*) [38]. Similar values are reported in the literature, obtained from different laboratory and field burns. The general conclusion is that the *critical*

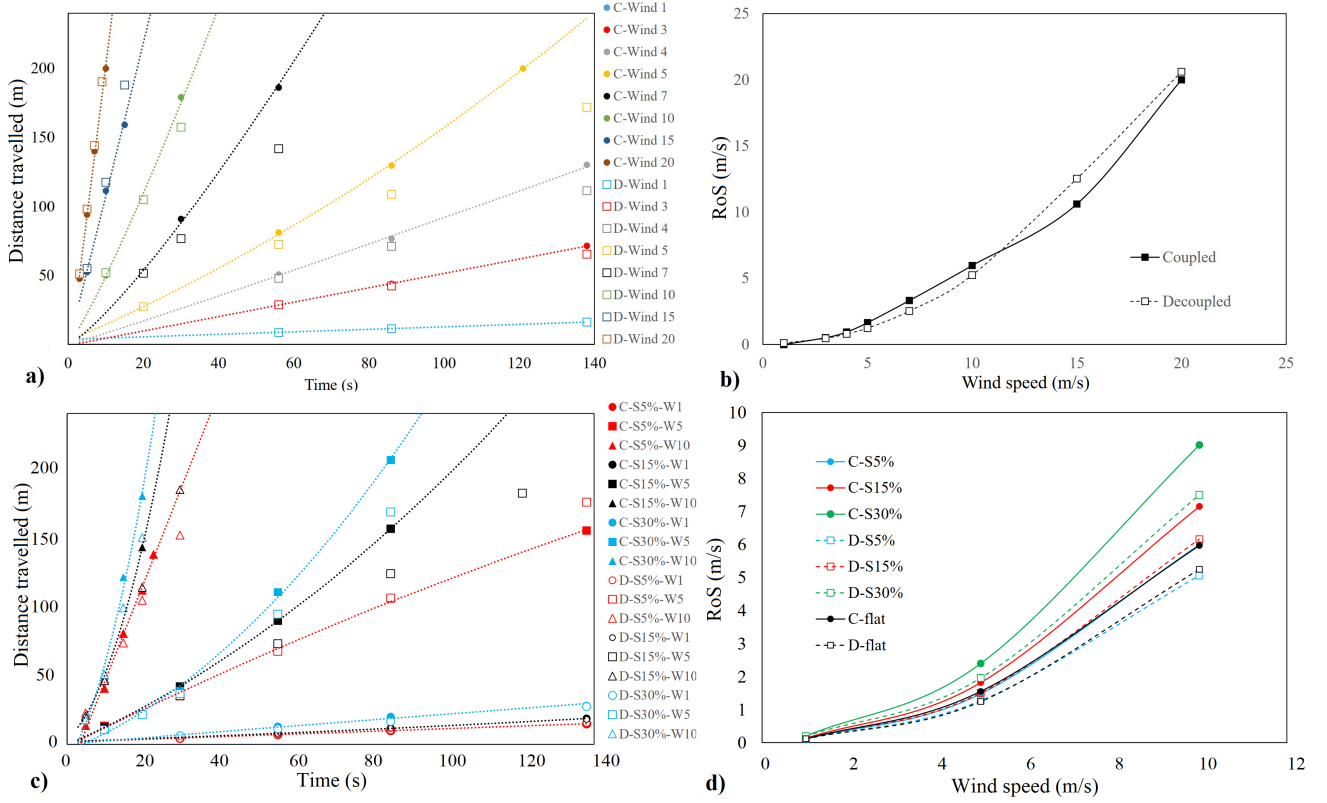


Figure 4: (a) Headfire position (distance travelled) for eight different wind speeds and (b) their corresponding RoS for horizontal topography; and (c) headfire position for nine different slope-wind combinations and (d) their corresponding RoS with fire propagating up slope. Both coupled (C) and decoupled (D) LS-FDS are tested in each case.

slope is in the 20°–25° range [35]. Even though LS-FDS does not model the flame or radiative heat transfer, the larger RoS predicted for larger surface slopes when coupling fire and wind models during uphill fire propagation is likely due to the released latent heat from the fire front inducing convective wind patterns up slope.

Thus, higher wind speeds and larger inclinations of the fuel bed lead to faster up-slope fire propagation. Coupled models predict higher values of the RoS than decoupled ones, presumably being able to better capture the relevant phenomena associated with fire-induced wind. Furthermore, Figure 5 shows that the shape of the predicted fire perimeter also differs, with the decoupled model displaying a smoother perimeter. This figure also confirms that the coupled wildfire model predicts faster propagation.

4. Enhancement for Decoupled Models

In Section 3, the influence that the fire has on the wind field has been shown to have a strong effect on its RoS, and therefore should not be neglected when predicting its propagation. Yet, this is precisely what decoupled wildfire models do. Aiming to capture the fire-wind interaction without incurring the hefty cost of solving the Navier-Stokes equations, a methodology is proposed here to enhance wildfire model predictions by providing it with near-surface wind

fields approximated from UAV measurements at higher altitudes. A top level description of the proposed methodology is shown in Figure 6.

4.1. System Overview

The proposed methodology is model agnostic, and therefore can be implemented as a stand-alone module to be integrated with any wildfire model that includes wind in its governing equations. Since its aim is to mimic the effect of fire-wind coupling, it is originally proposed with decoupled wildfire models in mind. Nonetheless, it could be applied to coupled models as well, potentially using data assimilation to correct the wind field predicted by the model. A top-level description of the methodology is shown in Figure 6 and summarised below:

1. A swarm of UAVs measure wind velocity at different 2D locations at flight height at a given time $t = t_i$.
2. The measured wind velocities are used to generate a high-resolution wind field using a data-driven super-resolution approach.
3. The high-resolution wind field at flight height is used to approximate the near-surface wind field by means of a mapping method such as a neural network.

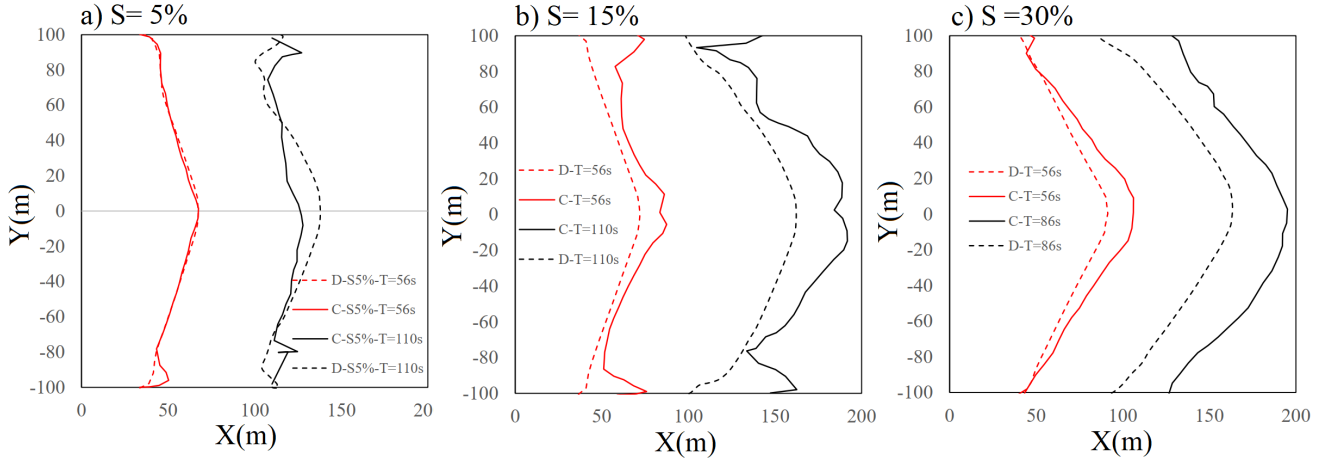


Figure 5: Fire perimeter as predicted by coupled (C) and decoupled (D) LS-FDS at three different times for three different slopes, namely (a) $S = 5\%$, (b) $S = 15\%$, (c) $S = 30\%$.

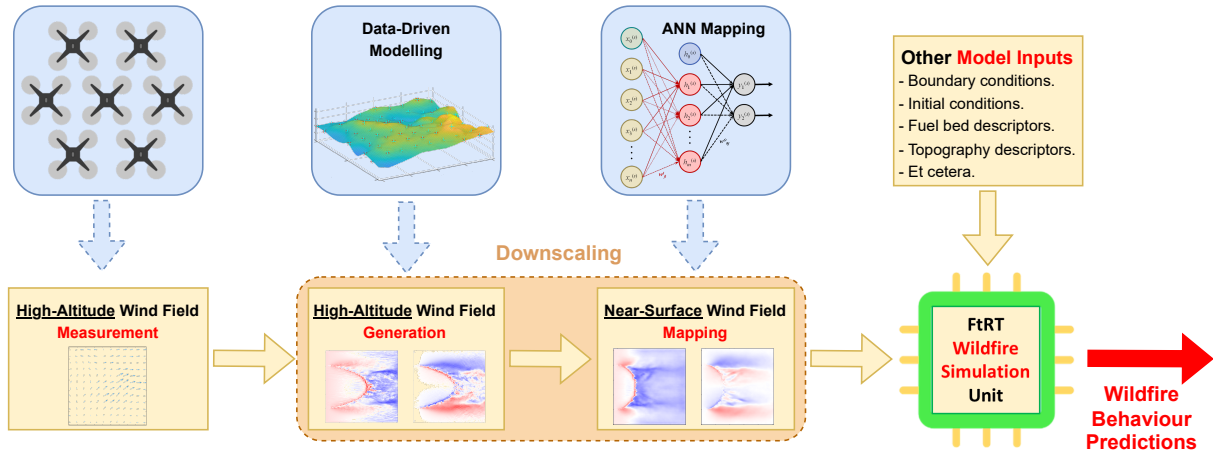


Figure 6: Top-level description of the proposed methodology to enhance decoupled wildfire model predictions using near-surface wind fields approximated from measurements at a high altitude (specifically, at flight height).

4. The downscaled near-surface wind field is fed into the FtRT simulator, which forecasts the fire propagation for the desired prediction horizon ($\mathcal{T}$). Thus, the fire propagation is simulated in the interval $(t_i, t_i + \mathcal{T}]$.
5. Once the desired time increment (Δt) for updates has elapsed, swarm-based measurements are re-taken at time $t_{i+1} = t_i + \Delta t$, and the process is repeated to predict the fire propagation in the $(t_{i+1}, t_{i+1} + \mathcal{T}]$ interval. Thus, the prediction horizon recedes by $\Delta t \ll \mathcal{T}$.

The fire propagation forecast during the prediction horizon ($\mathcal{T}$) can be used to assist firefighting operations, with the surface wind field remaining frozen during this time. Nonetheless, the outputs of the simulator after the time increment (Δt) has elapsed together with the updated near-surface wind field will comprise the inputs into the simulator, which can then forecast the fire propagation during the next $\mathcal{T}$.

Although it may be often infeasible to have a swarm of UAVs airborne solely to take wind measurements, equipping them with appropriate sensors (and possibly actuators) would enable the swarm to perform more than one task simultaneously. For example, consider the swarm of self-organising drones proposed by Innocente and Grasso [7] or the drone fleet system proposed by Ausonio et al. [29], which could easily be taking imagery and measuring environmental variables like wind, temperature or pressure whilst engaged in fire suppression and/or monitoring activities. Our preliminary vision of how the system in Figure 6 could blend into a potential fire management system is shown in Figure 7.

Evidently, the smaller the Δt between measurements the better, as the wind is kept frozen for shorter periods of time. A range of simulations are carried out in Section 5.1 to study the effect of Δt on a flat grassland covered with a uniform fuel bed. Since actual wind measurements are certain to be

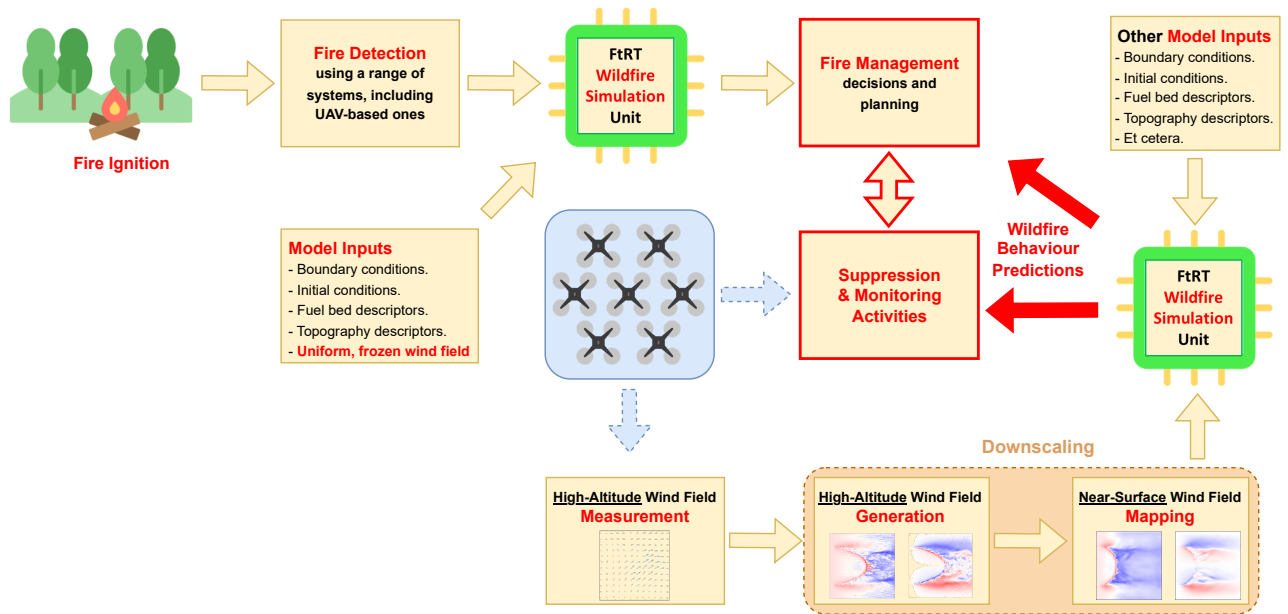


Figure 7: System view of an envisioned fire management system empowered by UAV swarms, which assimilates the proposed methodology shown in Figure 6 to enhance fire propagation model predictions.

uncertain, Section 5.2 provides an initial attempt at studying the effect of uncertainty on the wildfire model predictions.

4.2. Swarm-Based Wind Field Measurement

Current technology to measure wind velocities include traditional methods like cup anemometers and weather balloons, as well as more modern ultrasonic and laser-based systems. Conventional measurements above 60 m AGL require the building of costly towers, which motivates the use of alternative technologies such as *drone-mounted wind LiDARs* [23] and *drone-mounted ultrasonic anemometers* [24]. As opposed to mechanical anemometers, wind LiDARs measure the wind speed remotely, without direct contact with the atmosphere [39]. There are two types of Doppler wind LiDARs: (i) *continuous wave LiDARs* emit a high-frequency concentrated laser beam at the specified location for ranges of 10 m to 250 m AGL, whilst (ii) *pulsed LiDARs* generate a volley of low-frequency laser pulses so that wind velocity can be measured along a line at different locations simultaneously for ranges of 50 m to 10 km AGL [23].

Airborne atmospheric measurements may be taken using fixed-wing or rotor-based drones. The former are especially suitable for long-range and long-endurance flights, as they can reach considerably higher lift-to-drag (L/D) ratios. This translates to much lower thrust requirements than similar-sized rotor-based drones, and therefore to longer endurance [24]. On the other hand, rotor-based drones do not require a runway to take off, they offer greater maneuverability, and they have the ability to hover [21]. Measurements can be taken (i) *indirectly* by evaluating the drone response to the surrounding wind field [40], or (ii) *directly* by means

of dedicated sensors [22, 24]. The most common sensors used in UAVs include pitot tubes and multi-hole pressure probes [41], mechanical and sonic anemometers [40, 42], and LiDAR systems [23]. Wind speed measurement errors have been reported to be around 3% under horizontal inflows and ideally levelled conditions [40, 43], around 10–20% for harder situations [44, 45], and in the range of 20–50% when mounted on quadrotors [40].

Wetz et al. [22] proposed using multiple UAVs for synchronised wind velocity measurements in the atmospheric boundary layer (ABL), where a small swarm of 10 UAVs operate simultaneously to provide the spatial distribution in the vicinity of wind turbines. Their algorithm estimates wind velocity making use of the principle of aerodynamic drag and related quadcopter dynamics.

Since the air flow around a wildfire is highly turbulent and hot, it may be argued that flying drones in those regions presents a high risk of failure, especially for small-sized UAVs [46]. In order for the latter to cope with hazardous and all-weather conditions, there is substantial work being carried out on the design of more robust controllers [47] and of more resilient structures and materials [46, 48, 49].

This paper proposes the use of UAV swarms to periodically take multiple, simultaneous, real-time wind velocity measurements which will be subsequently used to construct the wind field to be fed into a wildfire propagation model. This removes the need to couple a wind model, and could be performed while carrying out other fire management tasks such as fire perimeter monitoring, fire suppression, or evacuation assistance. UAVs are particularly suitable because they do not require preinstalled infrastructure, whilst they

can carry a range of sensors, reach hard-to-access areas with ease, and keep human firefighters further away from danger. In turn, swarms are particularly suitable because they allow for multiple simultaneous measurements to help capture the general trend of the wind field. The specific UAV and sensor technologies to take the measurements and the swarming behaviour are beyond the scope of this paper.

4.3. Wind Field Downscaling

The accurate estimation of the wind field is of great importance in numerous applications. However, numerical weather models require powerful computing resources, which restricts the feasibility of fine-scale (high-resolution) forecasts [18]. This has led to coarse-scale weather models often being employed in wildfire decision-support systems. A domain-average wind field may be constructed using such models, usually in the form of uniform wind fields [50].

Downscaling methods aim to avoid costly high-resolution simulations across large geographic scales by inferring high-resolution from low-resolution data [18]. They may be either *dynamic* or *statistical* [51], with dynamic methods falling into either the *prognostic* or the *diagnostic* categories.

Prognostic methods such as those employed in numerical weather forecasting solve mass, momentum, energy, and moisture conservation equations and advance in time. They often include detailed models for the dynamics of boundary layers, land-atmosphere interactions, radiation, thermodynamics, and cloud processes. Therefore, these methods demand a substantial amount of computational power, have complicated initial and boundary conditions, and require highly skilled operators for their use [50, 52].

Alternatively, statistical downscaling makes use of results from large-scale simulations with coarse spatial resolution (*predictor data*) to derive predictions at smaller scales with fine resolution (*predictand data*). These methods are trained on a given set of predictor–predictand data pairs to learn the correlations between coarse and fine data [18]. Machine Learning (ML) and Deep Learning (DL) techniques are particularly useful in this domain. Specifically, Convolutional Neural Networks (CNNs) have found vast applications in downscaling atmospheric parameters such as wind fields for both, the construction of the wind field at a high altitude from point measurements [53] and the improvement of the wind field resolution [18, 54, 55]. Since the aim of the proposed methodology is to enhance predictions made by FtRT simulations, statistical downscaling methods are preferred. They can be trained in advance and be efficiently evaluated in real-time under operational conditions.

Since this paper aims to demonstrate how the proposed methodology enhances FtRT decoupled model predictions by providing them with multiple simultaneous wind measurements, the development and training of a specific statistical downscaling method is beyond its scope. Therefore, wind velocities are not actually measured and downscaled in this paper but extracted from three-dimensional (3D) high-fidelity physics-based Large Eddy Simulations in FDS.

Table 2

Wind field inputs/updates during a 120 s simulation of wildfire propagation for different values of the time increment Δt .

No. Wind Inputs	Δt (s)	Wind Input Times (s)
1	120	0
4	30	0, 30, 60, 90
6	20	0, 20, 40, 60, 80, 100
12	10	0, 10, 20, 30, 40, 50, ..., 100, 110
24	5	0, 5, 10, 15, 20, ..., 110, 115

5. Simulations and Analysis of Results

5.1. Enhancing Wildfire Model Predictions

A series of 3D grassland fire propagation simulations are performed using LPM-FDS and BFM-FDS (described in Section 2.1), with the resulting wind field extracted at different time-steps and provided to FireProM-F (described in Section 2.2) as if it were the output of the wind field downscaling module in Figure 6. The effect of feeding the decoupled wildfire propagation model with the wind field is studied for a range of time intervals between consecutive "measurement" updates (Δt).

Thus, the CSIRO C064 experiment is simulated using LPM-FDS and BFM-FDS with cell sizes of $1 \times 1 \times 1 \text{ m}^3$ and $0.5 \times 0.5 \times 0.5 \text{ m}^3$. Figure 8 shows the simulated wildfire at three time instants using $0.5 \times 0.5 \times 0.5 \text{ m}^3$ cells, with both models predicting similar RoS despite their different representations of the fuel bed. Since both simulators rely on LES to model turbulence, they include stochasticity and therefore predict fire perimeters which are not perfectly symmetrical. This is more noticeable on the flanks of the fire. Given that LPM-FDS is expected to be a more realistic representation of the real phenomena, and also that it appears to predict slightly more symmetrical fire perimeters, the wind "measurements" for the following experiments are extracted from the wind field generated by this model.

In order to investigate the effect of the time increment between wind measurements, the CSIRO C064 experiment is simulated with FireProM-F for 120 s and for five different values of Δt . The specific settings are provided in Table 2, whilst the temperature distributions are shown in Figure 9 at three points in time: 27 s, 53 s, and 100 s after ignition. In the first case, there is a single wind field input at the beginning of the simulation, which effectively means that the wind is frozen. The other cases consider decreasing values of Δt between measurements (and therefore between wind field inputs into the wildfire model) in order to somewhat account for the fire-induced wind without having to couple a computationally expensive wind model. For example, there are four wind field inputs into FireProM-F during the 120 s simulation for $\Delta t = 30 \text{ s}$.

The results for a uniform, frozen wind field are shown in Figures 9 (a), (b) and (c), providing a baseline against which to evaluate the effect of Δt . It can be observed that the fire front resulting from using a frozen wind field, thus

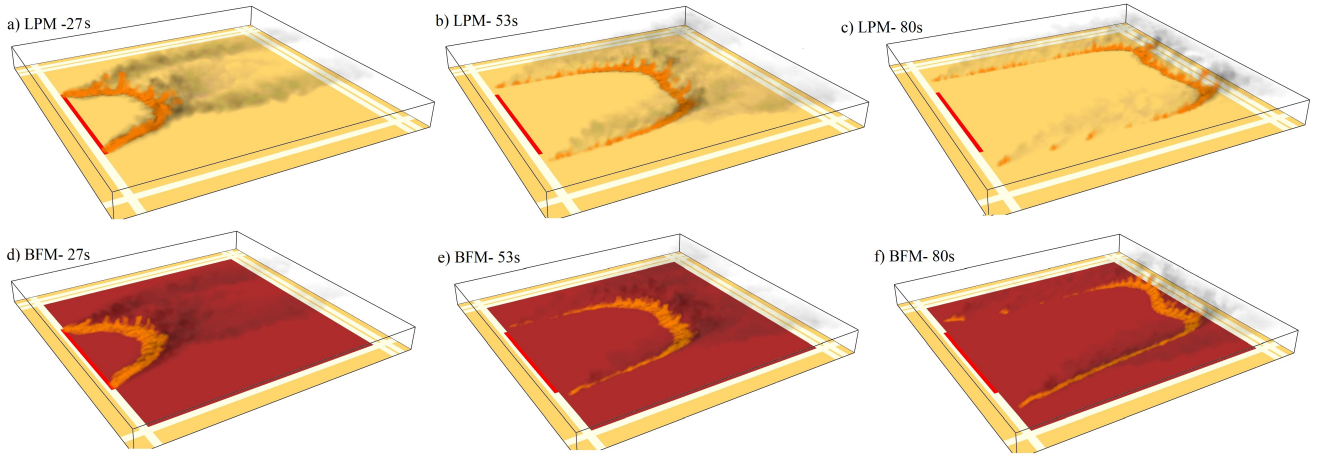


Figure 8: Simulated wildfire propagation at three points in time for the CSIRO C064 experiment using LPM-FDS (top) and BFM-FDS (bottom) models and $0.5 \times 0.5 \times 0.5 \text{ m}^3$ cells.

disregarding the fire-induced wind, has a pointy shape that differs from the actual and simulated shapes respectively observed in both, the field experiments and Figure 8. Instead, the proposed periodic update of the wind field constructed from measurements every Δt leads to more credible fire front formations. Comparing the shapes at $t = 27 \text{ s}$ in Figures 8 and 9, it is clear that smaller values of Δt (i.e. higher frequency of updates) predict more realistic shapes of the fire front. For larger values of Δt , the fire front reaches the counter-rotating vortex pairs which form downstream (not shown here), affecting the formation of the fire front and the pace of its propagation. Therefore, reducing the value of Δt , consequently increasing the frequency of wind field updates provided to the decoupled wildfire propagation model, may prevent or reduce the effect of this numerical (artificial) phenomenon. Furthermore, a visual comparison of Figures 9 (g), (h) and (i) ($\Delta t = 20 \text{ s}$), Figures 9 (j), (k) and (l) ($\Delta t = 10$), and Figures 9 (m), (n) and (o) ($\Delta t = 5 \text{ s}$) suggests that reducing Δt results in slightly faster propagation (i.e. higher RoS of the fire).

It is interesting to note that FireProM-F is deterministic. Therefore, the fire perimeter is symmetric for uniform wind (and uniformly distributed fuel), as can be observed in Figures 9 (a), (b) and (c). The asymmetries displayed in the remaining figures, in which the wind field is updated during the simulation, are due to FDS relying on LES to model turbulence (therefore introducing stochasticity). In fact, the fire perimeters predicted by LPM-FDS and by BFM-FDS in Figure 8 are also asymmetric. Recall that these simulated wind fields are taken as ground truth in the numerical experiments in this paper to represent actual measurements provided to FireProM-F to enhance its predictions. Furthermore, a given wind field extracted from the simulations corresponds to a specific point in time, which means that it is not time-averaged and is therefore affected by the oscillations of the dynamic combustion phase. This also contributes, albeit to a lesser extent, to the asymmetries observed in the simulated fire perimeters.

Figure 10 shows the simulated fire perimeter corresponding to the CSIRO C064 experiment at three points in time predicted by FireProM-F enhanced by wind field inputs derived from wind measurements every $\Delta t = 5 \text{ s}$ (red dotted lines). These predictions are in agreement with actual field measurements shown in the figure by black markers.

Figure 11 shows the size of the burned area at three points in time after ignition experimentally measured; predicted by LPM-FDS (coupled); predicted by FireProM-F (decoupled) with frozen and uniform wind; and predicted by FireProM-F (decoupled) enhanced by wind field inputs derived from wind measurements with different values of Δt . As can be observed, the size of the burned area simulated by LPM-FDS is larger than that of actual experimental measurements. One source of this significant discrepancy is the fact that the "atmospheric wind" velocities are variable both in intensity and direction during the field experiments, whereas they are kept constant during the simulations. Note that "atmospheric wind" here means without accounting for the fire-induced wind. It can also be observed that the burned area size predicted by the enhanced FireProM-F is closer to the one predicted by LPM-FDS than it is to the one experimentally measured. This makes sense, since the wind fields provided to FireProM-F were extracted from the LPM-FDS simulations. In fact, the smaller the Δt the better the agreement between them, whereas the decoupled Fire-ProM-F returns a burned area size similar to the one measured from the field experiments.

With regards to the computational effort, it is worth mentioning that simulating a wildfire propagation for a $100 \times 100 \text{ m}^2$ area discretised into 10,000 2D cells is performed up to 3.33 times faster than real time. That is to say that 1 min of wildfire propagation is simulated in 18 s on a single-core CPU. This may be reduced by orders of magnitude if implemented on parallel processing frameworks, which makes this approach especially suitable for operational settings.

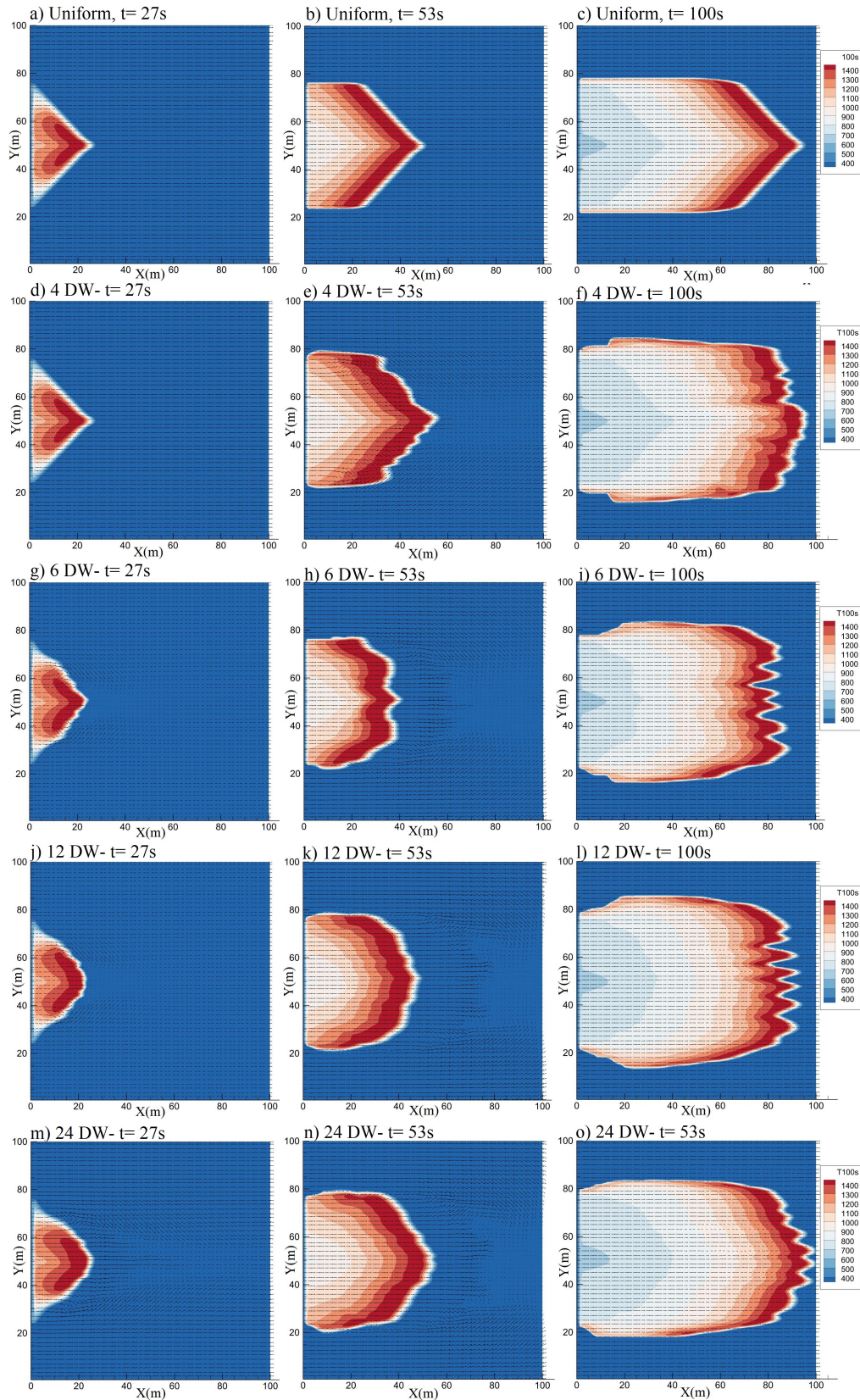


Figure 9: Temperature profile at three points in time from a 120 s simulation of the CSIRO C064 experiment by FireProM-F (decoupled) enhanced by wind fields inputs derived from wind measurements with update intervals (Δt) as in Table 2. Note that "X DW" stands for "X dynamic wind field inputs during the simulation".

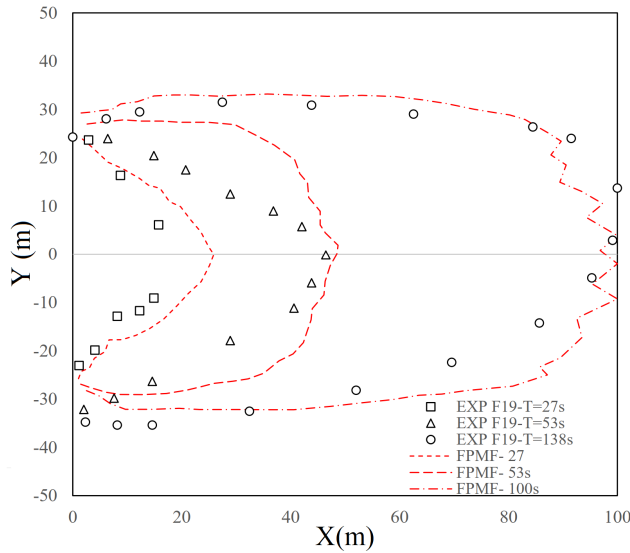


Figure 10: Three time instants of the CSIRO C064 experiment, where actual measurements are shown by black markers whilst the fire perimeter predicted by FireProM-F enhanced by wind field inputs derived from wind measurements every $\Delta t = 5$ s are shown by red dotted lines.

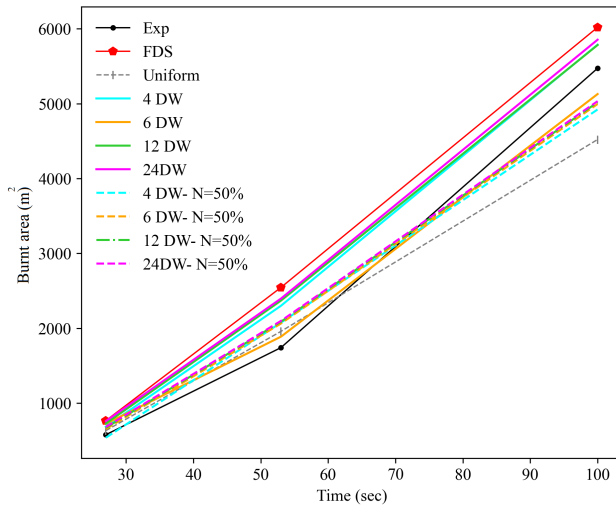


Figure 11: Burned area of CSIRO C064 experiment at three time instants after ignition experimentally measured, predicted by LPM-FDS (coupled), predicted by FireProM-F (decoupled) with frozen wind, and predicted by FireProM-F (decoupled) enhanced by wind field inputs derived from wind measurements with different update intervals (Δt). Note that "X DW" stands for "X dynamic wind field inputs during the simulation", whilst the percentage refers to Gaussian noise.

5.2. Effect of Wind Measurement Uncertainty

Wind speed measurement errors have been reported to be in the range of 20–50% when mounted on quadrotors [40]. In order to perform a preliminary study of the effect of

these measurement uncertainties on the simulated wildfire propagation, two scenarios are considered: (i) 30% and (ii) 50% Gaussian noise added to the "measurements". In other words, noise is sampled from a normal distribution with standard deviation equal to 30% and 50% of the wind velocity, respectively. Figures 12 and 13 show the temperature distribution at three points in time after ignition returned by FireProM-F simulating the CSIRO C064 experiment with noisy wind field inputs every 30 s and 10 s, respectively. As can be observed, the general shape of the burned area remains despite the noise, with the fire front displaying a more defined shape and faster propagation (higher RoS) for lower levels of noise (see also Figure 9). This is in agreement with the burned area decreasing when 50% noise is added to the "measurements" in Figure 11.

6. Conclusions

The accuracy of wildfire propagation models' predictions is influenced by numerous factors such as the fidelity of the fuel descriptors, adequate initial and boundary conditions, the coupling with atmospheric models, and the coupling with wind models such as Navier-Stokes equations to account for the interaction between wind and fire. This paper focused on the latter. More precisely, on enhancing the prediction accuracy of a given wildfire propagation model that is not coupled with a wind model—a.k.a. decoupled wildfire propagation model—by periodically providing it with wind fields constructed from UAV swarm-based wind measurements. This made it possible to account for fire-wind interactions without resolving computationally expensive mass and momentum balance equations as in full-blown computational fluid dynamics (CFD) simulations. This means that the decoupled wildfire propagation model predictions were enhanced while still retaining its ability to perform faster-than-real-time (FtRT) simulations to assist fire management operations.

A range of numerical experiments were performed to simulate the CSIRO C064 and F19 field experiments under different conditions and using a range of wildfire propagation models: (i) LPM-FDS (full-blown CFD simulator); (ii) LS-FDS (level set model within FDS); (iii) FireProM-F (2D physics-based simulator) with frozen wind field; and (iv) FireProM-F enhanced by periodic inputs of wind fields constructed from UAV swarm-based wind measurements.

Simulations performed using coupled and decoupled LS-FDS showed that coupling leads to higher RoS, closer to the values reported from field experiments. The difference in RoS increases with increasing atmospheric horizontal wind speeds and with higher terrain positive slopes. This is presumed to be due to coupled models being able to better capture fire-induced convective wind patterns up slope (i.e. downstream). Furthermore, the coupling of a turbulent wind model results, unsurprisingly, in the predicted fire perimeter being less smooth.

In order to study the effect of the proposed method to enhance decoupled wildfire propagation model predictions,

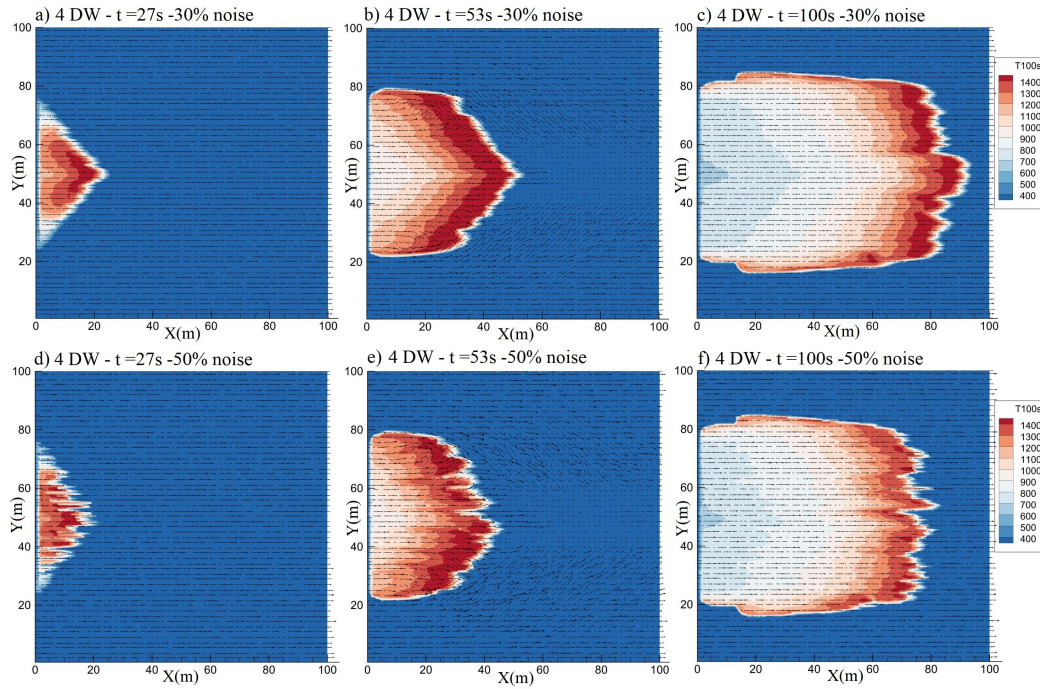


Figure 12: Temperature profile at three points in time from a 120 s simulation of the CSIRO C064 experiment by FireProM-F (decoupled) enhanced by wind fields inputs with 30 % (top) and 50 % (bottom) Gaussian noise with update interval $\Delta t = 30$ s. Note that "X DW" stands for "X dynamic wind field inputs during the simulation".

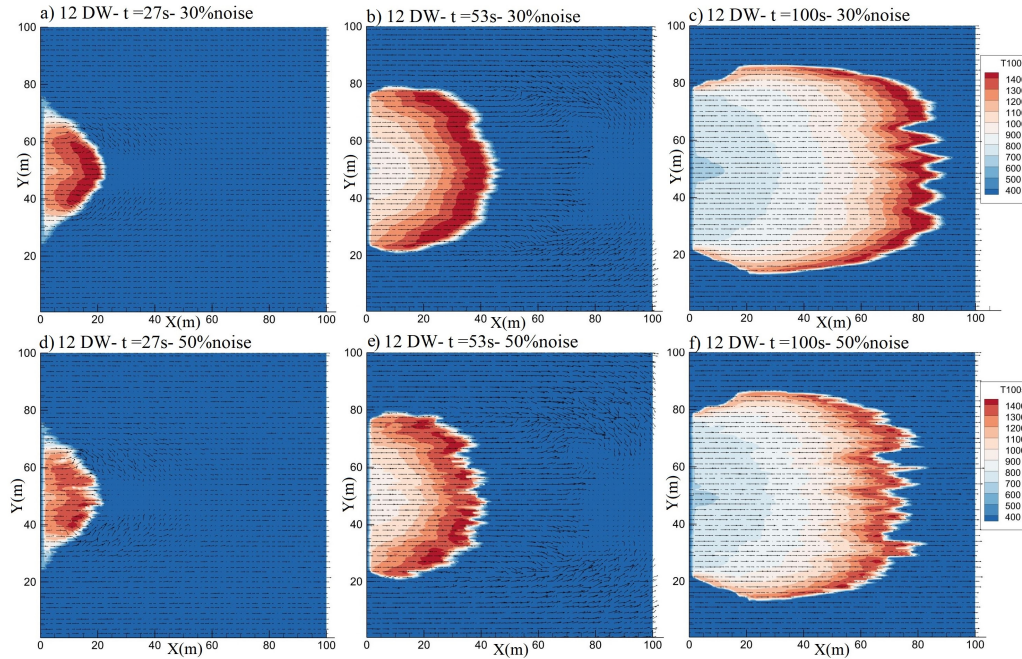


Figure 13: Temperature profile at three points in time from a 120 s simulation of the CSIRO C064 experiment by FireProM-F (decoupled) enhanced by wind fields inputs with 30 % (top) and 50 % (bottom) Gaussian noise with update interval $\Delta t = 10$ s. Note that "X DW" stands for "X dynamic wind field inputs during the simulation".

a series of wind fields generated by LPM-FDS were used to stand for actual wind measurements. FireProM-F was used as an example of a decoupled FtRT simulator whose predictions are to be enhanced by the proposed method. Thus, a

series of fire propagation simulations were performed periodically providing the model with "measured" wind fields. The resulting fire fronts and burned areas were then compared against those predicted by full-blown CFD simulations

(LPM-FDS), which were taken as ground truth because they provided the wind fields in place of the measured ones. Results demonstrate that the enhanced FireProM-F makes more accurate predictions than the plain one, and that the higher update frequencies, namely $\Delta t = 10$ s and $\Delta t = 5$ s, predict burned areas very similar to those predicted by LPM-FDS (ground truth). Furthermore, the fire front predicted by the enhanced FireProM-F was shown to track the experimental ones accurately. Since wind was not measured in the field for these experiments but extracted from LPM-FDS simulations, Gaussian noise was added to perform a preliminary study of the effect of measurement uncertainty. Results showed that the general shape of the burned area remains more or less the same when adding 30%–50% noise, with the fire front displaying a less smooth shape and slower propagation as noise increases.

CRediT authorship contribution statement

Mohammad Tavakol Sadrabadi: Conceptualization, Methodology, Software, Writing, Investigation, Visualization. **Mauro Sebastián Innocente:** Conceptualization, Methodology, Software, Writing, Supervision, Resources, Visualization.

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