Chapter 5
Simulation of Extreme Fire Event Scenarios Using Fully Physical Models and Visualisation Systems

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Abstract Although extreme wildland fires used to be rare events, their frequency has been increasing, and they are now causing enormous destruction. Therefore, understanding such fire events is crucial for global ecological and human communities. Predicting extreme fire events is an imperative yet challenging task. As these destructive events cannot be investigated via experimental field studies, physical modelling can be an alternative. This chapter explores the capability of fully physical fire models to simulate these events and the potential of integrating these simulations with advanced visualisation systems supported by machine learning. By presenting case studies and future directions, we emphasise the potential and necessity of this integration for improved fire management and policy making.

Keywords Canyon fire · Computational fluid dynamics · Data visualisation · Extreme fire · Junction fire · Large-eddy simulation · Physics-based model · Wildfire modelling · Wildfire visualisation

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5.1 Introduction

Wildland fires, fuelled by climate change and human activities, have increased in frequency and intensity. Most of these fires are limited in intensity and do not cause significant harm. On the other hand, extreme wildfire events can have catastrophic impacts on ecosystems, infrastructure and human lives. Therefore, it is important to understand these extreme events, which are dynamic and propagate with high speed and intensity. This includes understanding why such fires occur and the risks they pose, creating situational awareness and developing preparatory strategies.

It is almost impossible to develop such understanding via experimental studies—primarily because they are too dangerous and may lead to actual fire events that imperil the safety of researchers. Moreover, the equipment and probes to measure various parameters can be monetarily expensive and may get damaged during experiments. Additionally, many important parameters such as fire intensity, flame length, angle and height, flow direction and turbulence are difficult to measure. Fully physical fire models, though computationally expensive, have emerged as viable tools for studying such extreme events. These models include turbulent fluid motion, all modes of heat transfer (conduction, convection, radiation), pyrolysis (gasification of fuel from the solid state before taking part in combustion), combustion, soot production and firebrand transportation. All required physics and chemistry are accounted for when simulating fire-fuel and fire-atmosphere interactions. As a result, physical modelling offers insights into the intricate dynamics of extreme fire events and accurately predicts risk. Yet, the complexity of these models requires intuitive visualisation systems to make insights accessible and actionable and interpretations meaningful.

However, a system capable of rendering these complex datasets requires a sophistication not found in traditional weather visualisation systems. On the data processing side, the sophistication in size and dimensions requires extra handling steps. On the data presentation side, there is the need to represent the data in more than two dimensions (2D). Current representation standards struggle to capture a crucial characteristic of the fire phenomenon: their durational dynamics.

5.2 Extreme Event Scenarios

Extreme fire events are characterised by their unpredictability and severe impacts, having historically caused significant losses, especially in urban settings or in the form of fire tornadoes. These events challenge our predictive capabilities and response mechanisms. Historically, extreme fires were rare. However, in recent years, their frequency has been increasing and causing considerable social, economic and environmental catastrophes.

Extended fire seasons are anticipated to result in extreme fires becoming a regular occurrence (Di Virgilio et al., 2019). In 2003, two large bushfires (the McIntyre's

Hut fire and the Bendora dam fire) merged and advanced on Australia's capital, Canberra, causing severe damage (Sharples et al., 2012). In 2017, several active fire lines in central Portugal merged into a wildfire. They initiated a violent firestorm that cost 66 people their lives (Pinto et al., 2022). The 2018 wildfire season in the US state of California set an unprecedented record, with 95 fatalities and the destruction of over 22,000 structures. Its devastation is largely attributed to dynamic fire behaviours such as merging (Filkov et al., 2019). During Australia's 2019–2020 Black Summer, the fire near New South Wales's Badja Forest Road in Countegany merged with multiple other fires—including the Big Belimbla Creek and the Dampier State Forest fire (turning first into the Big Belimbla Creek fire) and then merging with the Bumbo Creek fire. This created the momentous Badja Fire Complex, which affected various regions of the NSW South Coast. Fire merging was a critical factor in catalysing destructive winds and, in one case, led to the formation of a fire-generated vortex (Peace et al., 2021).

Predicting and preparing for such events presents numerous challenges. One of the primary difficulties is the limited historical data that could provide a robust foundation for a fast and mostly accurate prediction model. The impacts of global climate change further complicate matters as they alter traditional fire patterns and intensify fire risks, increasingly making empirical prediction models obsolete. The intricate interactions between factors such as vegetation, weather, topography and human activities add complexity to fire predictions, which require either full-physical modelling or parameterisation of physical modelling into empirical prediction models. Moreover, as urban areas increasingly encroach on wildlands, the potential for devastating fires affecting human populations increases, requiring intricate fire management and evacuation planning. Coordinating responses across multiple jurisdictions, each with its unique set of protocols and priorities, requires detailed mapping and collaboration, ensuring that communities are adequately protected from the unpredictable nature of wildfires (Davis et al., 2021).

Resource constraints pose another significant challenge. Maintaining readiness for extreme events, especially when frequent smaller fires already stretch resources, is daunting. Furthermore, conveying the risk of these uncommon but extreme events to the public is often challenging due to comprehension of low probability events, variable risk perception and desensitisation to warnings—to name but a few factors. This leads to potential complacency and a lack of preparation (Mackie, 2014; Hanson-Easey et al., 2019). Raising public awareness through powerful visualisation can be a key solution.

5.3 Physical Fire Models: An Overview

Forest fire models have been developed since the 1940s and differ widely in complexity. They can be divided into three categories: empirical, semi-empirical and physics-based.

Empirical models use past experiences and intuition to predict the behaviour of future fires. Semi-empirical models evaluate the properties of a steady “surface fire through a homogeneous solid-fuel layer, [such as the rate of spread (RoS) and the flames’ height], based on an energy balance written in an inertial reference frame [attached to] the fire front (Rothermel, 1972). The main advantage [of such models] is [their] simplicity” (Morvan et al., 2022), which is why the Rothermel model is applied in FARSITE (Finney, 1998), the world’s most widely used operational tool. FARSITE is a 2D fire propagation model that deploys a vegetation layer that accounts for a terrain’s topography. It includes a vegetation library covering various ecosystems (e.g. grass, litter, shrubs, etc.). However, it is important to note “that the experiments used to calibrate the constants [of semi-empirical models] were performed only at a small scale, [i.e. in] solid fuel litters. For various reasons ([including] compactness of the fuel layer, low level of turbulence, [dimensions of the] vegetation layer, etc.), the conditions [of] such experiments [prevent the use of semi-empirical models for all configurations observed at field scale. This] motivated different research [teams to] couple a simplified fire-spread model (such as Rothermel’s) with a [meso-scale atmospheric model (e.g. Filippi et al., 2011). This approach is considered very promising] for operational applications [that require] the simulation of wildfire propagation [at a] regional scale. [It is still being refined with] new (more physical) fire propagation models” (Morvan et al., 2022) emerging, such as elaborations of Balbi et al.’s model (2009).

More fundamental research is needed to foster a deeper and more nuanced understanding of wildfire behaviour and its underlying physics. Within limits, this may be developed via experimental fires. Yet, numerical simulation using fully physics-based models shows more promise. Examples of these are FIRETEC (Linn & Cunningham, 2005), FireStar3D (Morvan et al., 2018), FireFOAM (Edalati-nejad et al., 2022) and FDS (McGrattan et al., 2023). “Most of these models are based on a [multi-phase] formulation, assimilating the vegetation [cover] to a sparse, porous [medium] and [solving] a set of [balance] equations governing the behaviour of the coupled system formed by the vegetation and the surrounding ambient air” (Morvan et al., 2009). Grishin (1997) initiated this approach.

Physics-based models consist of two sets of differential equations, each describing the evolutions of the fluid and the solid mediums, coupled through interaction terms in the mass, momentum and energy equations. The first set of differential equations describes the evolution of the composition of the vegetation (i.e. solid fuel) as it is “subjected to the intense heat flux coming from the flaming zone” (Hassan, 2022). The second set of partial differential equations describes the evolution of a turbulent-reactive fluid flow, which results “from the mixture of the pyrolysis and combustion products with the ambient [atmospheric air]” (Morvan et al., 2018). Due to this high level of complexity, physics-based approaches are currently “limited to simulating fire behaviour at [local field] scale (i.e. a few hectometres). [They are only applied to studies that aim to improve] knowledge of wildfire dynamics (Frangieh et al., 2020) and to fire safety engineering studies [of structures located] at the wildland-urban interface. Their degree of complexity also increases the level of uncertainty of the [predicted results derived from physics-based

Table 5.1 Summary of main characteristics of four fully physical fire models

	FireStar3D	FDS	FIRETEC	FireFOAM
Solver	3D implicit	3D explicit	3D explicit	3D implicit
Low Mach model	Yes	Yes	No	Yes
Turbulence	TRANS/LES	LES	LES	LES
Turb./rad. interaction	Yes	Yes[a]	Yes[a]	No
Combustion model	Yes	Yes	No[b]	Yes
Multiple-fuel model	Yes	Yes	No	Yes
Small-scale	Yes	Yes	No	Yes
Field-scale	Yes	Yes	Yes	Yes

[a]The radiation heat transfer is increased empirically
[b]Pyrolysis and combustion occur at the same location without transport into the gaseous phase (as discussed in Hassan, 2022)

models]. Therefore, as in other [computational fluid dynamics] applications, it is [necessary] to enforce the confidence [attribute to the] results obtained" (Morvan et al., 2022) by regularly comparing them to experimental data (e.g. Frangieh et al., 2018; Hassan et al., 2023). An overview of the differences and similarities between fully physical fire models used in the literature is summarised in Table 5.1 (Morvan, 2011).

5.4 Visualisation Techniques Used in Physical Modelling

Given the complexities of physical models for different weather phenomena, there is a real need to push the limits of scientific visualisation to meet user needs. For example, the modelling software *FireStar* (Morvan & Dupuy, 2001), a simplified version of *FireStar3D*, generates 2.5D plots by animating traditional 2D plots. These representations allow the visualisation of changes in flow fields, such as velocity or temperature. This configuration provides some improvement over traditional 2D visualisations. However, they are limited when representing data derived from mathematical functions (Tirado Cortes et al., 2023).

Similarly, FireStar3D and FDS allow 3D visualisation of weather phenomena such as heat release, smoke and particles. This representation enables a multi-perspective view, which provides a superior analysis of weather phenomena that 2D representations cannot provide (Kraus et al., 2020). These tools also animate the outputs to increase the information communicated to the user. Still, new issues arise, such as interaction design and how it can significantly improve the user experience.

In both instances, immersive visualisation provides superior capabilities. First, it places the user inside the event, allowing them to interact with the environment through a multisensory experience (Ens et al., 2021). Second, viscerally experiencing a weather event such as a wildfire permits users to explore data meaningfully and to develop insight into the mathematical formulas that determine these events

(Lee et al., 2021). Immersive visualisation pushes for a realistic representation of the data, allowing observation of fire behaviours that easily get lost when data is abstracted and condensed for non-immersive setups (Marriott et al., 2018).

5.5 Case Studies

We have explored several specific modelling and visualisation scenarios. Their dynamic modes of fire propagation are shown in Fig. 5.1. We simulated four configurations of merging fires using two fully physical models: FireStar3D and FDS. The fire line lengths of the V arms are 50 metre. The scenarios include merging two-line fires, fire coalescence and eruptive fire behaviour in canyons. We used FireStar3D to model a surface fire and its propagation in Erica shrubs litter. On the other hand, we used FDS to model fire propagation in raised fuel (involving 6-metre-high Douglas fir trees with 4-metre crowns, standing on 0.5-metre-high Kerosene grass). The fuel types are characterised by specifying their thermo-physical and flammability properties.

RoS and energy (i.e. heat) release are the two important factors determining a fire's degree of devastation. Fast fire propagation and heat intensity can quickly engulf houses and communities at a moment's notice. As a result, built structures

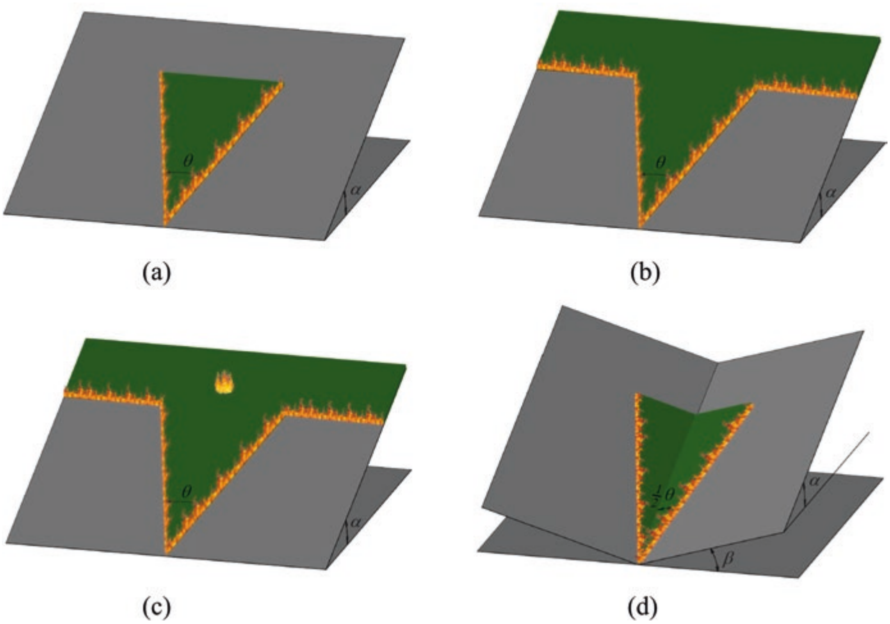

Fig. 5.1 Four merging fire configurations that are considered in this work: (**a**) junction fire on sloping terrain, (**b**) junction fire on sloping terrain with shoulders, (**c**) junction fire merging with a spot fire and (**d**) junction fire in a canyon

and human and animal lives can be lost. Smoke production can hinder evacuation efforts due to low visibility and cause long-term health effects due to its release of toxic particles. These three aspects are presented quantitatively and/or qualitatively in this chapter.

Figure 5.2 presents junction point propagation (left axis) and time evolution of the total heat release rate (HRR—right axis) obtained using the FireStar3D model. Using Tecplot software (2023), fire spread is visualised in Fig. 5.3 using the distribution of the solid-fuel bulk density at the vegetation cover surface. Flames are visualised by an iso-value "surface of the soot volume fraction [coloured] by the gas temperature. An [iso-value] surface of water-[vapour] mass-fraction [visualises smoke]" (Badlan et al., 2021). We can observe that up to ~15 s, the junction point propagates identically for cases (a–c). After that, case (a) with no shoulder propagates faster than the "with-shoulder" scenario (i.e. case b). We can observe a sudden jump in case (c), as the spot fire merges with the junction fire. The initial peak in the HRR is due to the ignition phase. As cases (b) and (c) had the same amount of burnable vegetative fuel, almost identical HRR is observed, indicating that the spot fire's contribution is not significant. The canyon fire (i.e. case d) propagates much slower

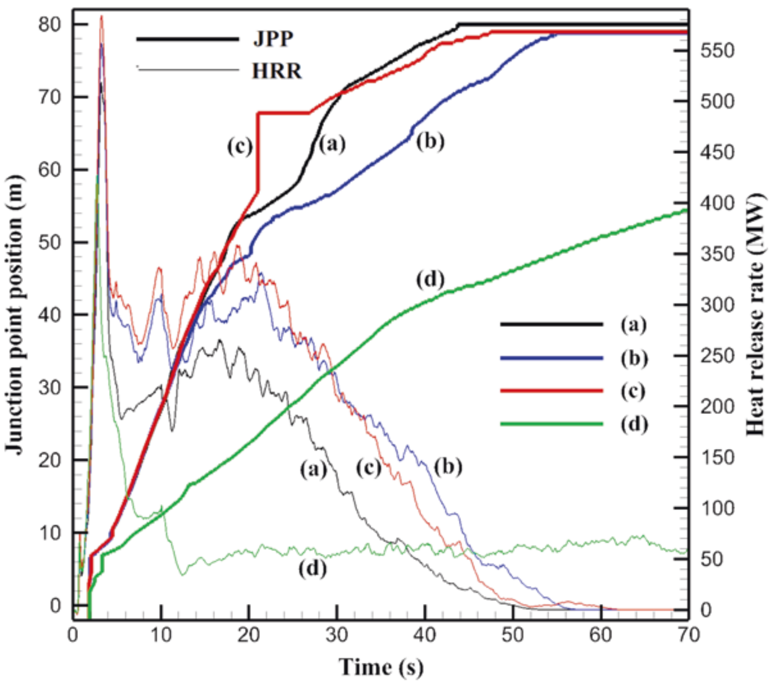

Fig. 5.2 Time evolution of the junction point position (JPP) and of the total HRR obtained in the four configurations shown in Fig. 5.1, using the FireStar3D model: (**a**) junction fire on sloping terrain, (**b**) junction fire on sloping terrain with shoulders, (**c**) junction fire merging with a spot fire and (**d**) junction fire in a canyon

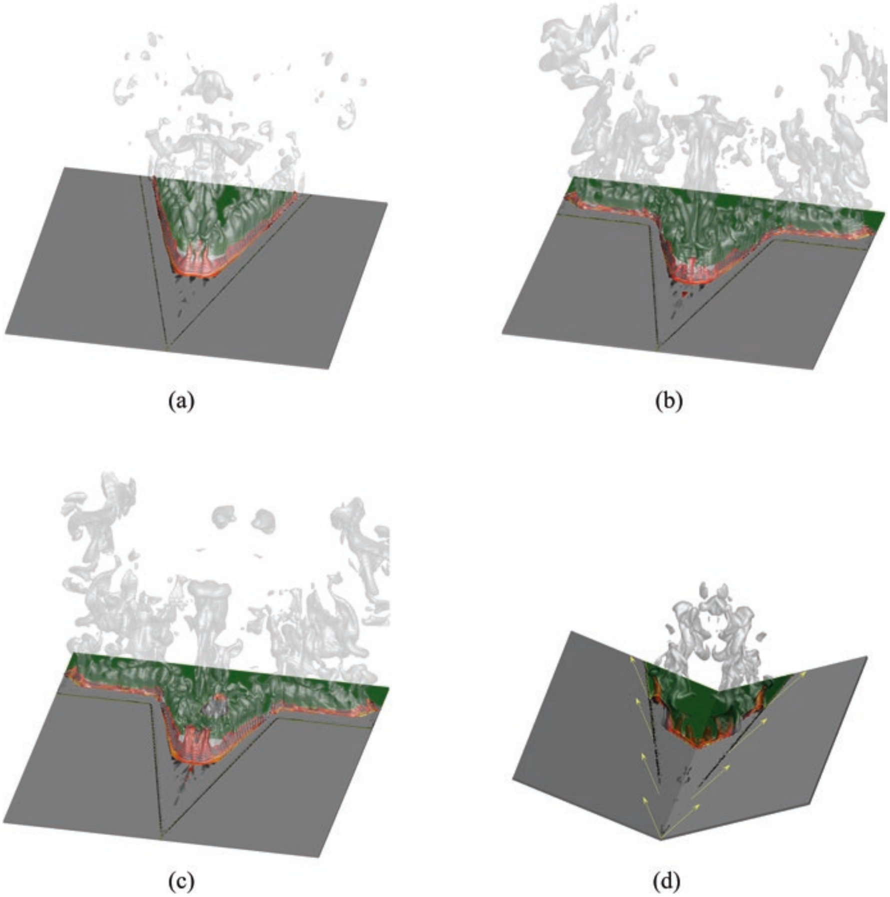

Fig. 5.3 Visualisation of four fire configurations shown in Fig. 5.1, using the FireStar3D model: (**a**) junction fire on sloping terrain, 15 s after ignition; (**b**) junction fire on sloping terrain with shoulders, 15 s after ignition; (**c**) junction fire merging with a spot fire, 15 s after ignition; and (**d**) junction fire in a canyon, 60 s after ignition

than the others. This is because a canyon fire follows the lines of the steepest slope (shown by the arrows in Fig. 5.3d) intersecting with the junction arms, which blocks fire propagation in this favoured direction. Comparing (a) and (c), after 5 s, a significant reduction of HRR is observed for the canyon fire. We can also observe in Fig. 5.2 that flame intensity and heat release are much lower than in the other cases.

With the FDS model, the canyon fire scenario was not modelled because the model currently does not have a clear ability to simulate slopes in multiple directions. The other three scenarios show similar quantitative behaviour (regarding JPP and HRR) observed in surface fire scenarios simulated by FireStar3D.

Figure 5.4 shows scenarios after 25 s from ignition that are visualised using the FDS companion software Smokeview. It shows junction fires represented by ignition lines. Flames and smoke are visualised by iso-value surfaces of the heat release rate per unit volume (>80 kW/m^3) and smoke extinction opacity (1000 m^2/kg), respectively. We can observe merging behaviour with intense flaming and large smoke billowing. If we set smoke extinction opacity to 8000 m^2/kg (i.e. the default value of Smokeview), more dramatic smoke billowing can be observed. However, it will obscure flame propagation.

Using Smokeview, animated 2D plots of flow fields (i.e. velocity, temperature, vectors, etc.), which are gas phase parameters, can be visualised. Similarly, we can visualise animated 2D plots of solid phase parameters, such as heat flux and temperature. These can provide insight into the physical phenomenon associated with fire propagation. In Fig. 5.5, 2D temperature plots along the domain's centre line are presented, giving viewers an idea of properties such as flame inclination, height, temperature distribution, etc. Additionally, 2D plots of radiation heat flux on the surface are presented, which can inform about the heating or cooling of the surface via radiation or convective processes. Legends for contours are presented in Fig. 5.5c. Figure 5.5 also includes 3D flames.

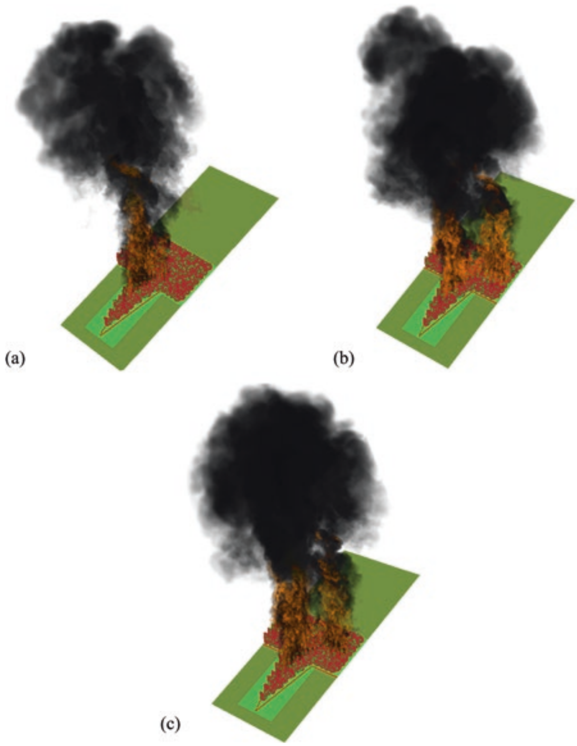

Fig. 5.4 Visualisation of the three configurations simulated using the FDS model: (**a**) junction fire, (b) junction fire with shoulders and (**c**) junction fire merging with a spot fire. All are on sloping terrain. Bright green and moss green surfaces represent burnable and non-burnable grass, respectively. Red and green particles represent tree crowns

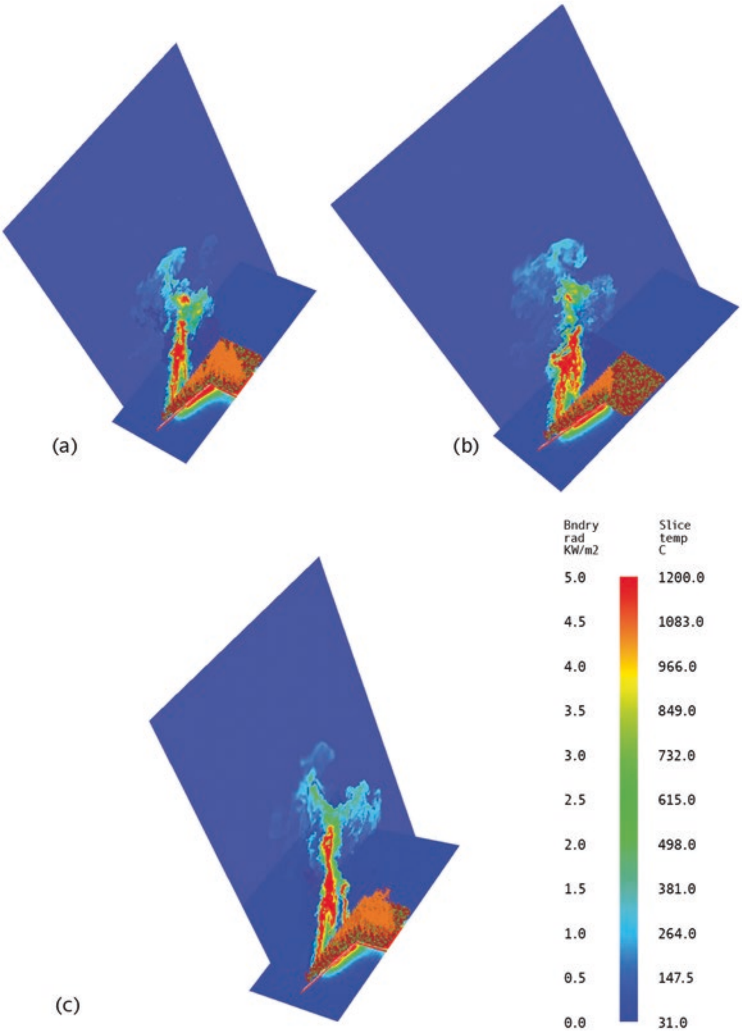

Fig. 5.5 Visualisation of 2D and 3D data from simulations, using FDS: (**a**) junction fire on sloping terrain, (**b**) junction fire on sloping terrain with shoulders and (**c**) junction fire merging with a spot fire. 3D flame data, 2D gas temperature through a vertical plane and 2D radiation heat flux data on the surface are presented. Time = 20 s from ignition

5.6 Integrating Simulations with a Visualisation System

A visualisation that can represent the complexities of such data is necessary to take full advantage of the recreation of wildfire events with physical models. However, the main challenge for visualising such models is the complexity of the data. For this reason, data integration methods are required to unlock new capabilities for powerful new visualisation approaches.

There are multiple benefits to improving the visualisation of physical models. First, they can facilitate new insight into the complex correlations between the natural environment and human ecologies. Second, they can illustrate scenarios that can educate and help plan damage control for at-risk communities. Finally, they inform society about the hypothetical future scenarios and how to prepare for them.

Physical models require a major processing complexity compared to other models (e.g. semi-empirical), given the high dimensionality of the data. Yet, these modelling systems are the only ones capable of plausibly reproducing wildfire behaviour (Badlan et al., 2021). Hence, an approach is needed to process their outputs into visually compelling form.

On the data side, the main limitation is the file size, which poses the biggest technological challenge when translating data on the manifold phenomena occurring during wildfires into visualisations. One potential solution is using Geostack (Hilton & Garg, 2022), a powerful geographic and weather data management tool. It is the core driver of SPARK (Miller et al., 2015), an empirical fire modelling application used widely across Australia. Geostack provides potent data handling and organisation utilities to manipulate the complex outputs of a physical model in ways that cater to visualisation. Software libraries such as Zarr, a Python programming language library, can support this translation by efficiently managing and compressing large data files.

On the visualisation end, *Unreal Engine* (UE) is the only tool capable of handling realistic representations of weather phenomena at such scale. UE is a game engine that has emerged as a new standard in VFX production. It excels at handling vast amounts of data without diminished performance. This commends it for application to physical modelling output. UE can recreate complex interactions and process multiple information layers without losing realism in its representation. Further, UE also facilitates the integration of multiple hardware, allowing a visualisation system to run across multiple platforms. This increases its appeal for a larger pool of potential users with different application needs, e.g. firefighters using an immersive-screen virtual-reality simulation trainer or fire behaviour analysts using the visualisation as part of their regular desktop-based reviews.

5.7 Future Directions

The current state of data visualisation and immersive technologies has led to the formation of immersive analytics as a new area of research (Dwyer et al., 2018). This area uses spatial interaction, collaboration and multisensory presentation to explore complex datasets, granting enhanced visualisation workflows compared to traditional 2D and 3D visualisation systems (Saffo et al., 2023). Future research should focus first on developing best practice conversion methods for the outputs of physical models so that an immersive analysis system can harvest them optimally. When designed right, such a system is poised to provide a superior learning experience compared to traditional workflows.

Another opportunity to explore in future research is enhancement of immersive visualisation using machine learning (ML). It promises to provide alternative approaches to overcoming the constraints of physical modelling, namely, the processing time and size of their data outputs. ML is already being used to improve fire modelling systems' accuracy and processing time by combining satellite images of active fire data with image processing-based predictions within geographic regions (Cheng et al., 2022). However, this image processing approach is limited because it must assume that all information and intricate physical processes represented by active fire satellite images are being encapsulated. This is not the case as it oversimplifies the complex physical processes and interactions involved in fire spread.

Another promising application domain of ML is the emerging modelling direction method known as physics-informed neural networks (PINNs). It involves the integration of fundamental physics principles into neural networks to enhance performance while reducing the demand for extensive data and computation time (Raissi et al., 2023). For instance, Ren et al. (2022) trained generative adversarial networks (Goodfellow et al., 2014) on large-eddy simulations. They achieved the incorporation of physical partial differential equation losses to simulate turbulent reactive flow. This could help speed up the processing times of physical models. Another application of PINNs in fluid dynamics involves an auto-encoder neural network model for interpolating low spatial-temporal resolution data to high resolution while adhering to physical constraints (Bode et al., 2021). This improves the efficiency of modelling of complex phenomena.

These ML methods attempt to reduce the barriers to applying physical modelling for visualisation. A line of research is already looking at how to apply these algorithms (Endert et al., 2017; Wang et al., 2022; Wang & Han, 2023). He et al. (2020) even presented a prototype pipeline from data collection and processing through ML training to visualisation. These all used simplistic and hypothetical simulations of fluids under very controlled scenarios. Future work should consider adapting these findings for wildfires and extreme weather event visualisation.

5.8 Conclusion

Extreme wildfire events are increasing in frequency, causing significant losses and challenging predictive capabilities and response mechanisms. Therefore, enhancing scientific insight and raising public awareness through wildfire visualisation is important. 3D physics-based models can provide the high-fidelity data required for such visualisation. For this chapter, we simulated four merging fire configurations using the FireStar3D and FDS models. The fires were visualised using obtained field variables, such as radiation heat flux, gas temperature fire intensity and smoke. While capable of reproducing wildfire behaviour, 3D physics-based models still pose challenges due to the complexity and size of their data. This also has repercussions for their visualisation. Tools such as Geostack hold promise since they have already been used for handling large amounts of data in other weather management applications, e.g. *SPARK*. Their full realisation depends on other cutting-edge technologies, such as UE, that can provide additional processing power. The VFX capabilities of the engine provide the necessary tools to recreate these datasets accurately. Finally, technologies such as ML can speed up the generation of new reliable data, overcoming the processing time limitations that currently afflict the work with physical models. Overall, using these methods at the data level of a visualisation system can support the creation of accurate representations while improving its overall performance. Eliminating the time-to-generate-data bottleneck can greatly improve the usefulness of the visualisation system and, thus, facilitate the generation of new knowledge. Finally, ML can be key to developing novel interaction methods, such as manipulating and reviewing data in real time during a visualisation session, which is currently not possible.

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