

Deep learning-based wildfire spread prediction

This work is using deep learning techniques and remote-sensing data to predict wildfire spread dynamics over a time sequence of real-world cases. Increasing availability of remote-sensing data and better computational resources means that deep learning-based methods have the potential to deliver accurate and timely predictions of the progress of large wildfires.

Problem: Given several fire-related features (e.g., fuel, weather, topography) and the fire extent at time t as inputs, determine the fire extent at time $t + 1$.

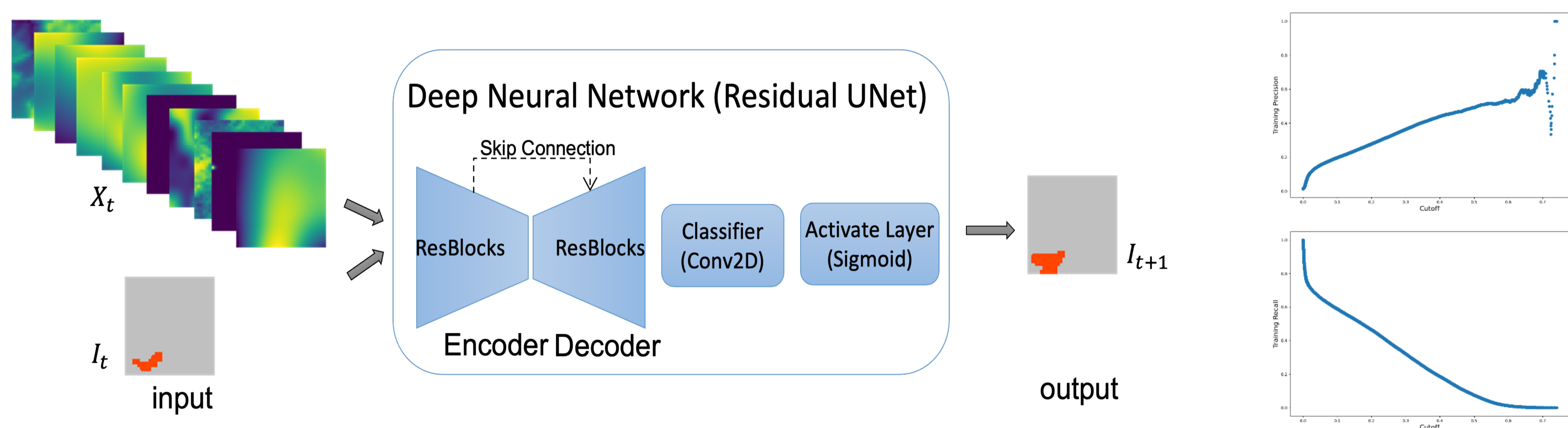


Fig. 1: Left: Wildfire spread prediction framework (FireNet-1). I_t is the fire extent at time t , X_t are the fire-related features. The output I_{t+1} is the wildfire spread prediction at time $t + 1$. Right: Precision and recall training diagnostics for the deep learning model.

Dataset: Public real-world data from Google Earth Engine (GEE) – next-day-wildfire-spread

Metrics: Precision, recall, AUC(PR)

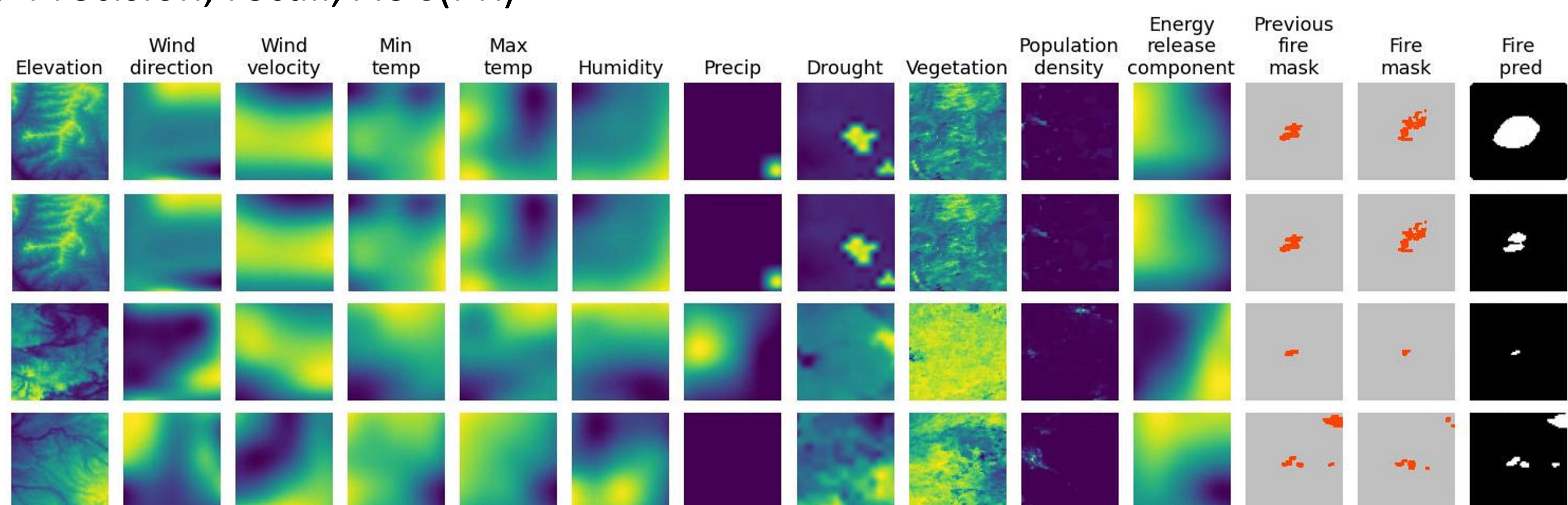
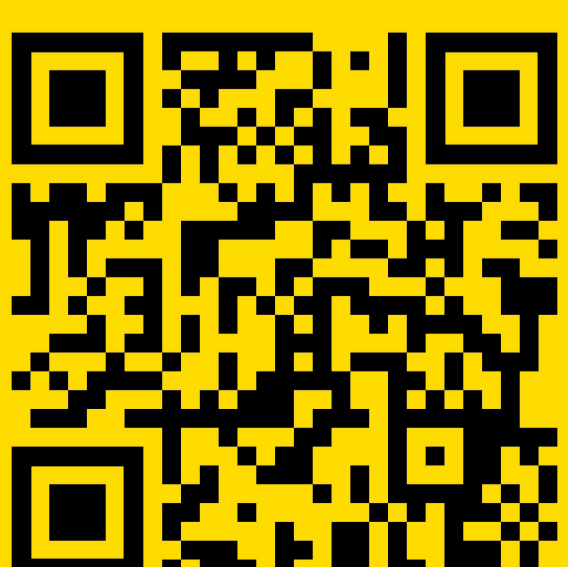


Fig. 2: Deep learning model (FireNet-1) results on the Next-Day-Wildfire-Spread dataset

Future work will consider a **multi-task framework** (FireNet-2), which can improve the representability of the network by exploring more supervision information, thereby improving the overall performance.

We will also build a real-world **time-series** fire spread dataset and benchmark existing data-driven approaches, which can be promoted by the research community to develop more data-driven models for wildfire prediction.





This research is investigating how random fluctuations in environmental conditions influence wildfire propagation and how we can better account for these sources of uncertainty in predictive models. This will allow fire managers to better assess bushfire risk and support improved public warnings and more effective allocation of firefighting resources.

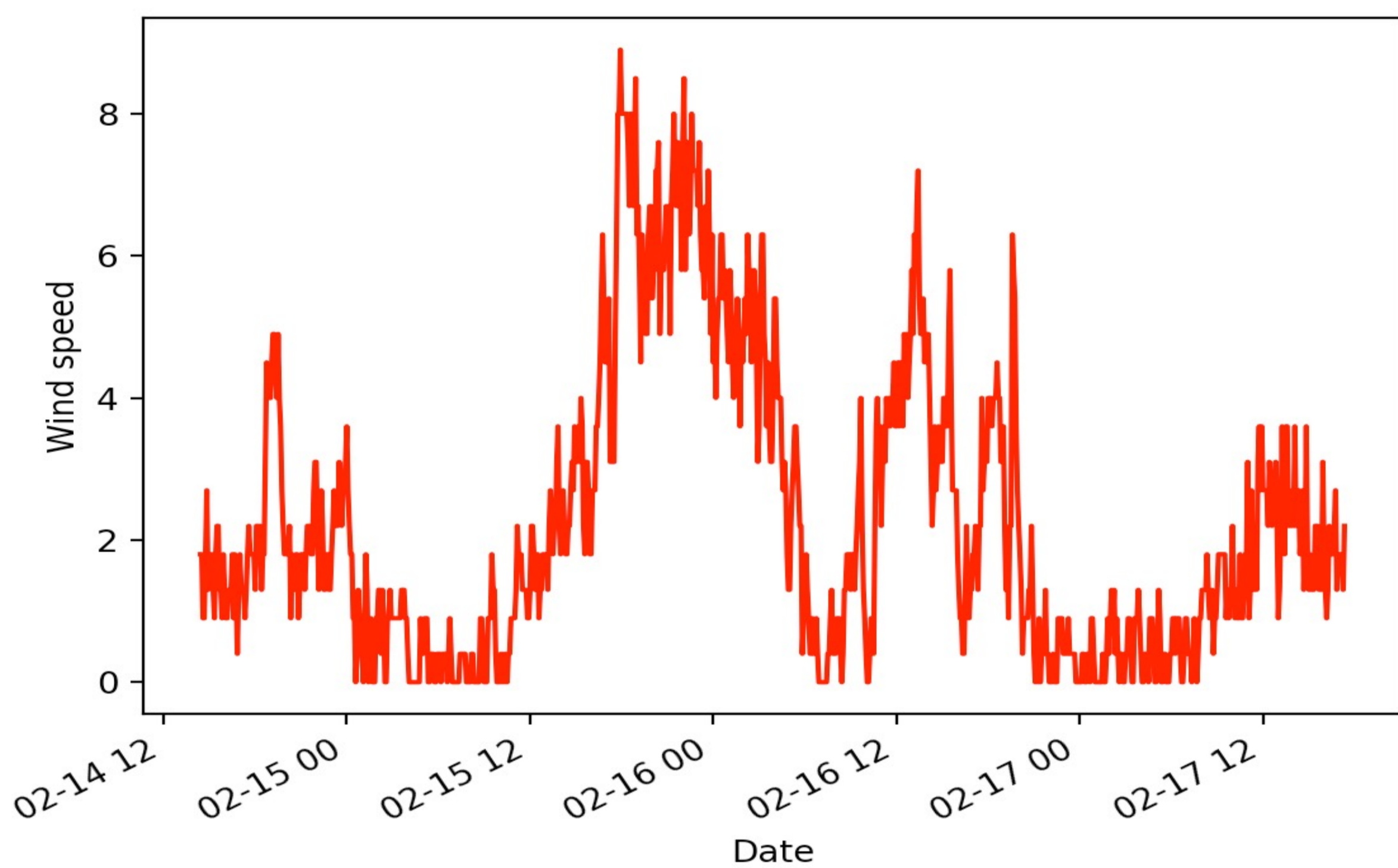


Fig. 1: Observed wind speed data showing sub-hourly fluctuations that can influence the rate and direction of fire spread.

Environmental factors such as wind speed and direction can fluctuate randomly over space and time (see Fig. 1), yet current bushfire prediction methods tend to rely on single deterministic values. To better account for these uncertain effects, a mathematical model was developed and integrated with Australia's national fire spread simulation platform, Spark. This enhanced model effectively captures the uncertainty associated with variable weather inputs, and validation studies have demonstrated the new model can generate predictions that better agree with real-world observations.

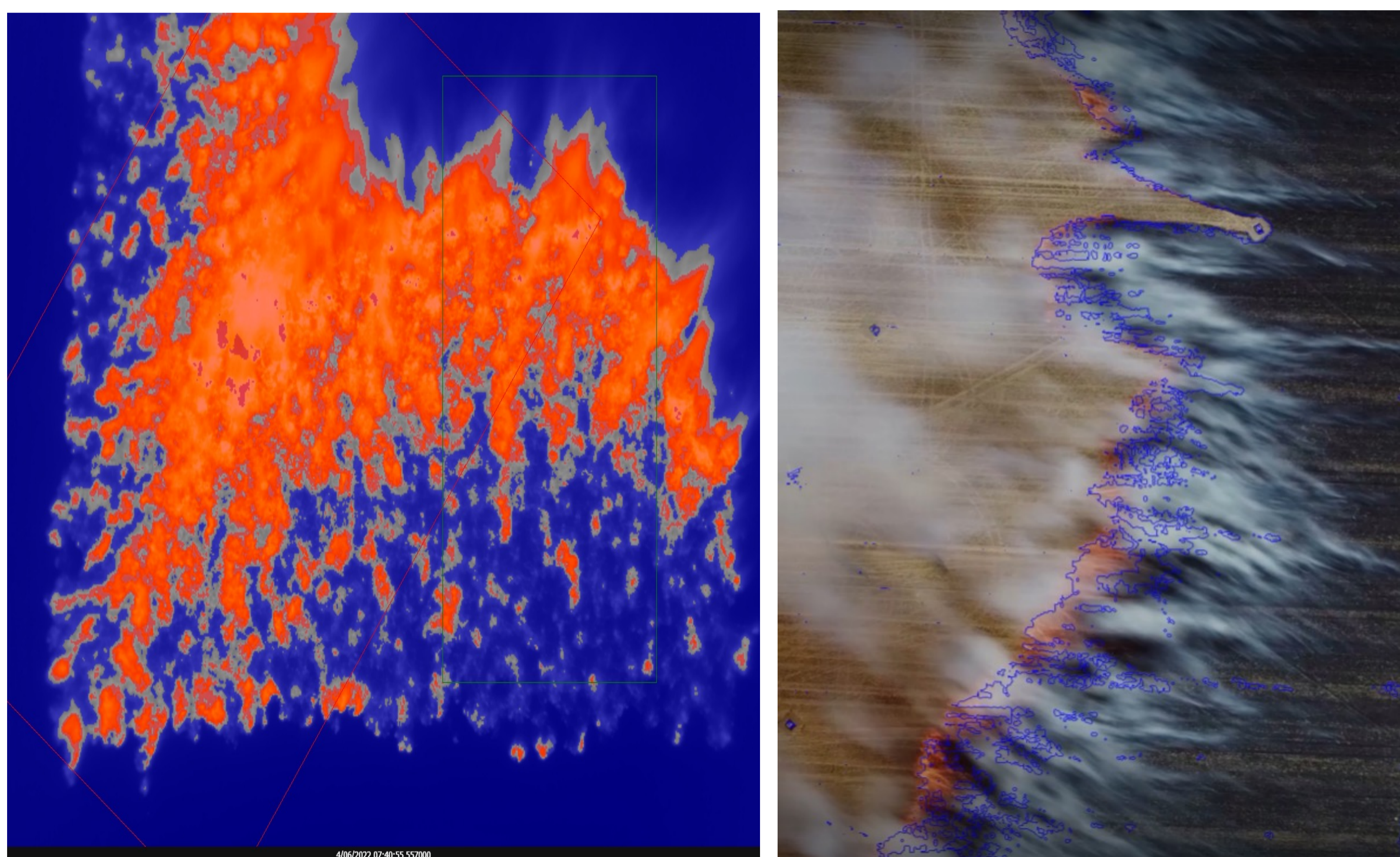


Fig. 2: Thermal infrared data (left) from experimental fires in wheat crop stubble (Uni. Melb). Video still (right) of large-scale experimental fire in crop stubble conducted by colleagues from SCION NZ Forest Research.

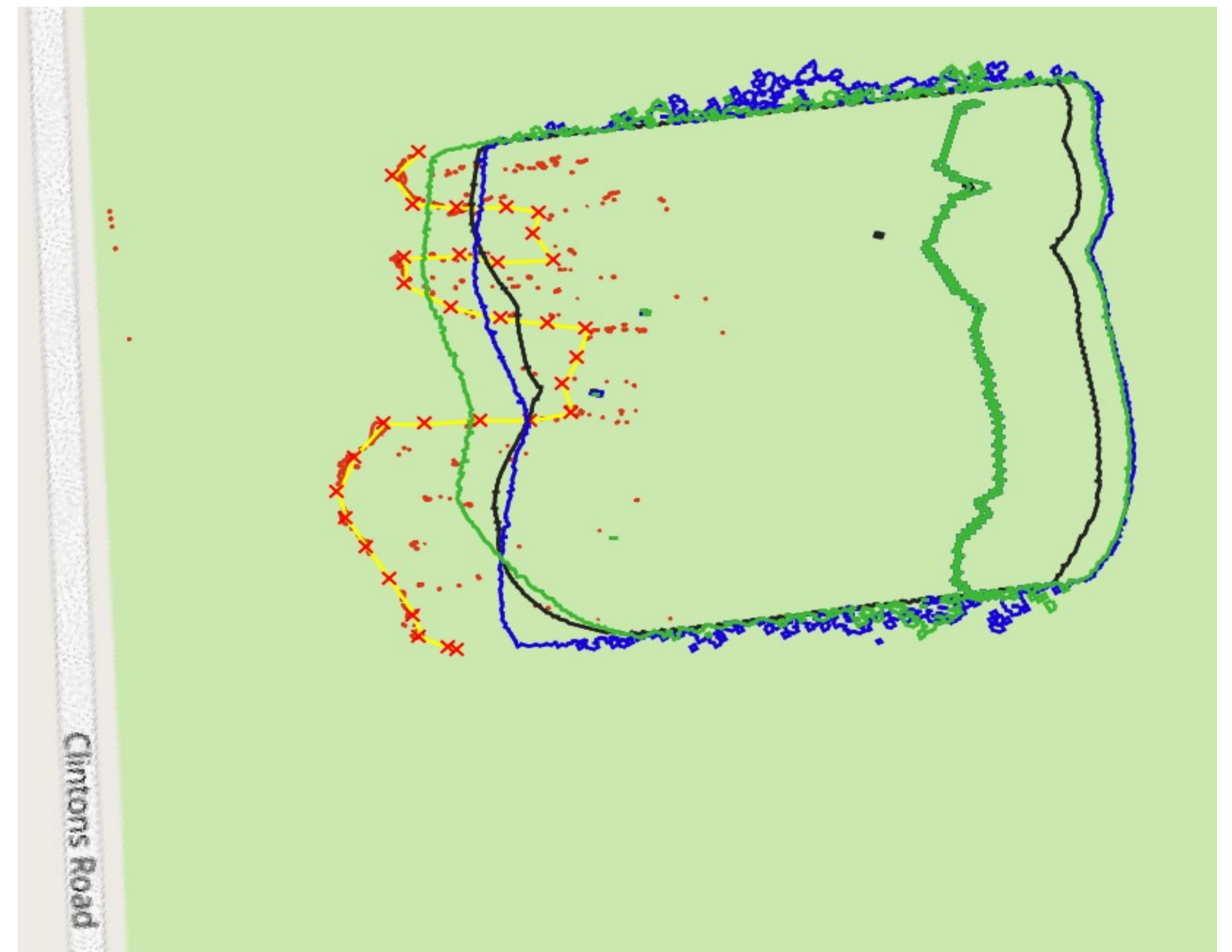


Fig. 3: Simulations of experimental data provided by SCION NZ Forest Research. The yellow line with red crosses shows the experimental data, while the green blue and black lines show the simulated fire.

In addition to incorporating hourly and sub-hourly fluctuations in wind speed and direction, the new mathematical modelling approach can also account for other sources of uncertainty and for dynamic effects such as fire-generated air flows. As such, the modelling approach is better able to capture the realities of fire propagation, including many aspects that are currently overlooked in operational platforms.



Simple indices for assessing the moisture content of fine, dead fuels

This research evaluated and compared several simple models for estimating the moisture content of fine dead bushfire fuels, such as litter and woody debris. These models provide a quick and reliable way for fire crews to assess flammability and likely fire behaviour.



Fig. 1: A surface fire burning through litter and coarse woody debris.

The moisture content of litter and woody debris is a key determinant of fire potential and fire behaviour. Obtaining reliable estimates of the moisture content of dead fine fuels is therefore a critical requirement for effective fire management. It is particularly important in determining whether ignitions will develop into wildfires, their subsequent rate of spread, and other factors such as the likelihood of spotting, crown fire transition and extreme wildfire development.

While more sophisticated models exist, simple models for fuel moisture content are easier to implement and support better conceptual understanding within acceptable limits of accuracy. One class of simple models is defined in terms of the **fuel moisture index (FMI)**, which is a function of the difference between air temperature T ($^{\circ}\text{C}$) and relative humidity H (%):

$$FMI = 10 - 0.25(T - H).$$

Another class is defined in terms of **vapour pressure deficit**, which is the difference between the amount of moisture in the air and the maximum amount of moisture the air could hold.

Figure 2 shows how various models performed against fuel moisture data collected in the ACT.

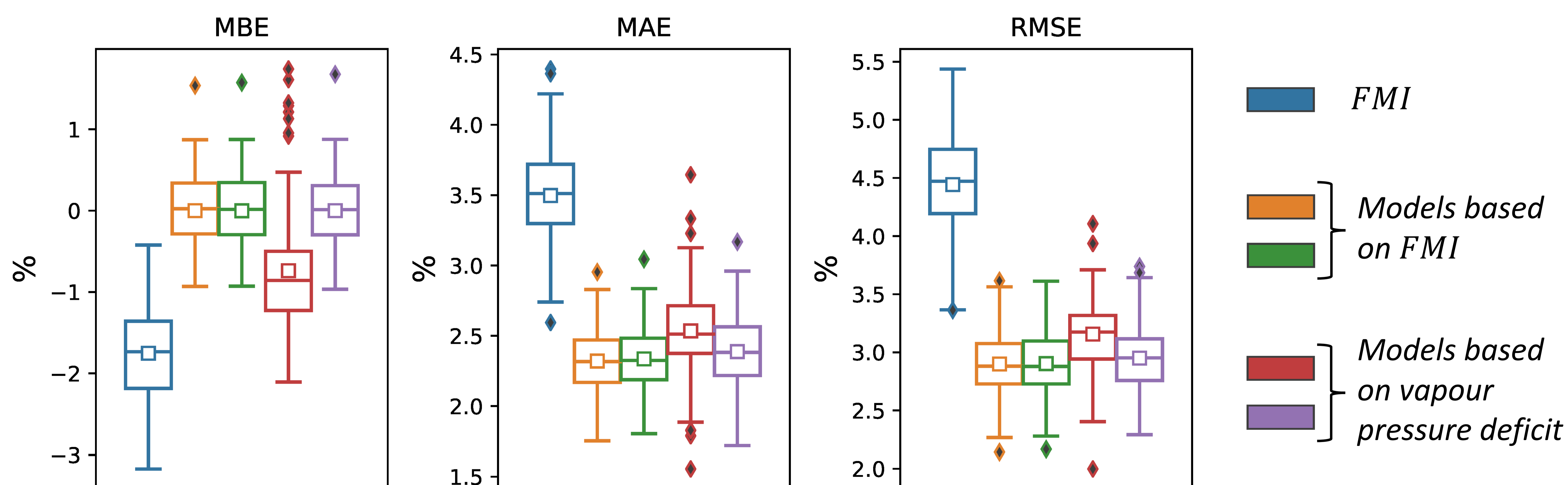


Fig. 2: Error statistics showing the models based on FMI perform just as well, if not better, than models based on vapour pressure deficit. MBE = mean bias error; MAE = mean absolute error, RMSE = root mean square error.



Better prediction of crown fires in pine plantations

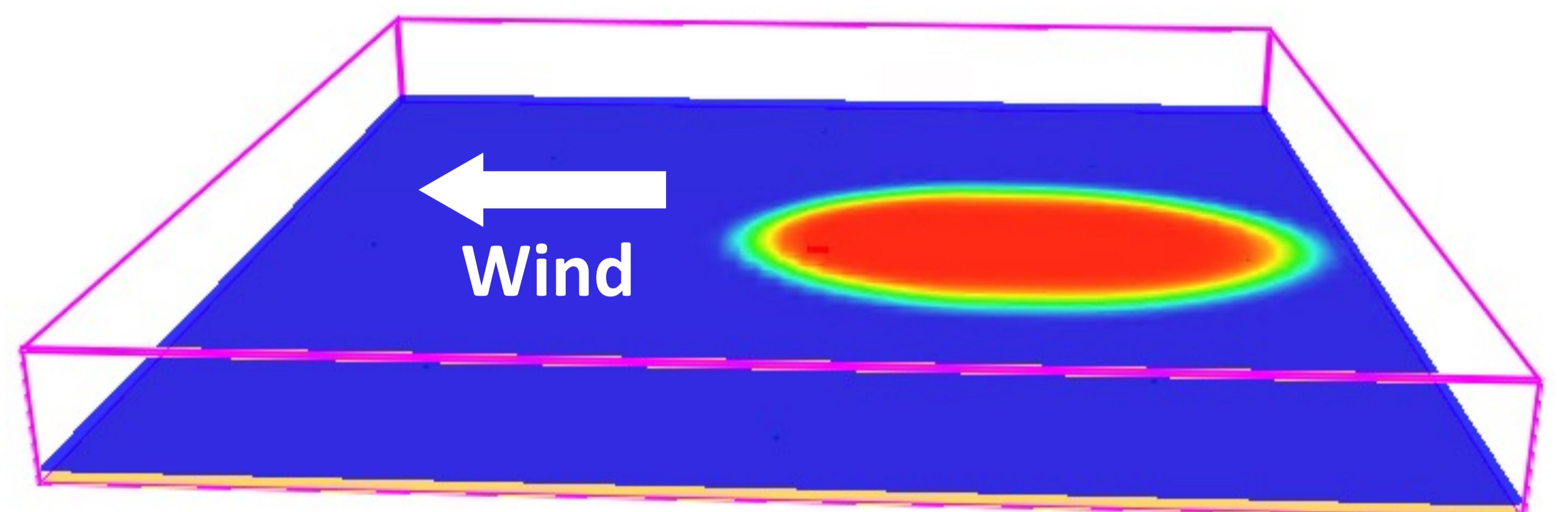
This research aims to extend existing models of crown fires in pine plantations to improve outcomes in fire prediction, fire suppression and plantation management.

Crown fires are one of the more common types of dynamic fire behaviour, occurring in many significant fire events such as Black Saturday. Crown fires occur when a fire becomes extreme enough for the flames to transition from only burning the surface and near surface fuel layers to also consuming the canopy. They are particularly dangerous since they spread many times faster than surface fires, and can also significantly increase ember generation, which can exacerbate spotting ahead of the main fire front. Crown fires can occur in many vegetation types, including eucalypt forest and **pine plantations**.



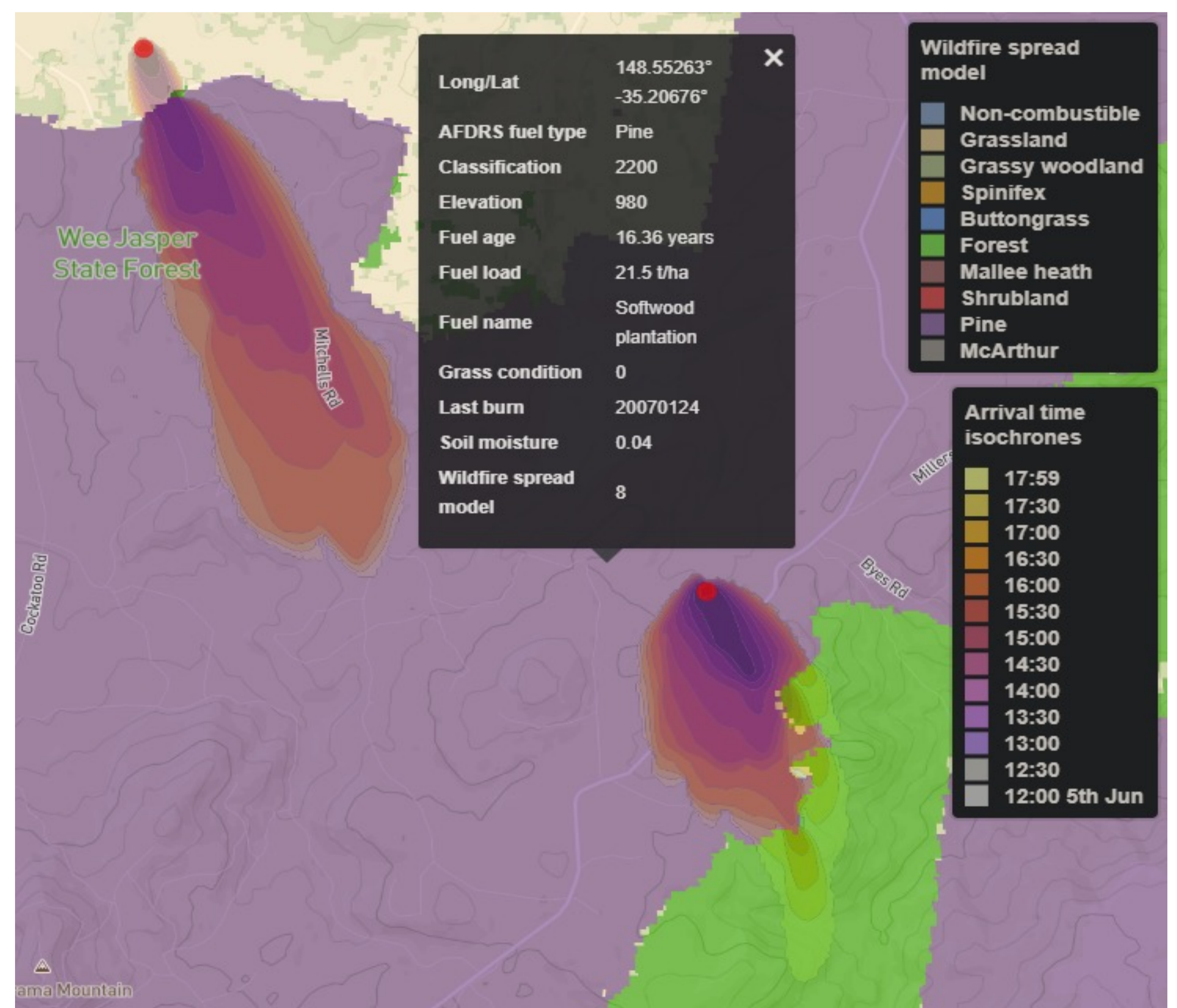
Existing research into crown fire occurrence is generally restricted to one-dimension, with the likelihood of a crown fire (along with its rate of spread) given by an empirical model, semi-physical model or physical model. To extend existing crowning models for use in two-dimensional simulations, issues such as **how much of the fire is likely to crown**, how to model oscillation between crown and non-crown fire phases, and how crowning behaviour effects the overall shape of the fire, need to be addressed. Addressing these issues will improve the accuracy of crown fire simulations.

Physical models, which capture combustion, heat transfer and fluid dynamics are being utilised to determine the mechanisms which cause crown fires, and how much of the fire is likely to crown.



A basic physical model of a wind driven elliptical fire

These will be distilled into simplified equations and implemented in the **Spark** wildfire modelling framework, which forms the basis for Australia's new national wildfire simulation system. The resulting model will support decision making in real time as well as plantation planning and management via the use of ensemble analyses.



A simulated grass fire spreading into a pine plantation (NW ignition) and a fire started in pine spreading into eucalypt forest (SE ignition) in Spark



iFire: An AI wildfire visualisation system for research and training

This work is using artificial intelligence to develop iFire, an immersive and interactive visualisation system for wildfire-related research and training. In particular, the system will support visualisation of extreme wildfire events, which are the forefront of international research efforts, and whose unpredictability challenges insight and operational decision making.

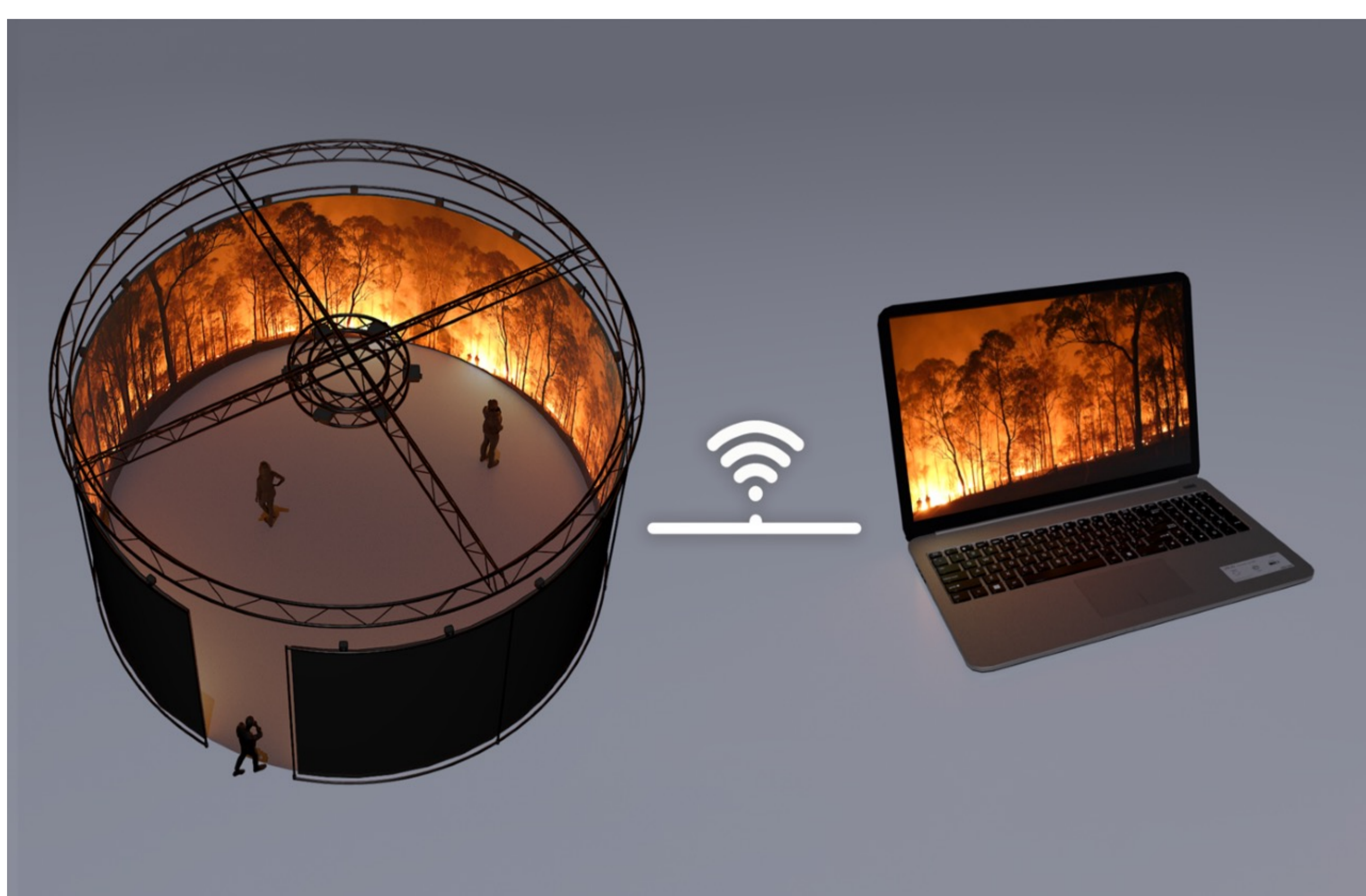
Wildfires are becoming increasingly extreme and unpredictable, burning with high intensity at unprecedented scales. They are able to create their own weather systems and rare phenomena such as fire tornadoes.

These behaviours signal the age of violent pyroconvection, where fires are no longer isolated incidents but a climatic force. Their unforeseen dynamics challenge existing forms of visualisation.



Immersive Visualisation for Research

Immersive visualisation provides an enhanced experience, allowing researchers to viscerally and cognitively navigate wildfire scenarios as if they are present. Fire scenarios driven by artificial intelligence can deliver visualisations that can deepen the understanding of complex dynamics by translating their unforeseen evolution into tangible phenomena.



Immersive Training for Frontline Personnel

iFire produces training environments that simulate unexpected fire behaviours in real time, fostering enhanced situational awareness for fire personnel faced with the potentially erratic behaviour of extreme wildfires.

Complemented by an interactive system that monitors and classifies the actions of decision makers, iFire can automatically adapt scenarios for training needs.

In addition to enhancing situational awareness, these self-adapting scenarios can help improve collaborative decision making for frontline personnel and incident managers.

