THE UNIVERSITY of EDINBURGH
Digital Research Services

2025 DRS AMBASSADOR

Internship Scheme

Fire Engineering & Physics-informed ML

Ambassador: Nishant Gaur | Institute for Infrastructure and Environment (IIE), School of Engineering | College of Science and Engineering

Host: Dr Zak Campbell-Lochrie | School of Engineering | College of Science and Engineering

Contents

Abstract

Wildfires have been a significant focus in past few years due to recent high-profile incidents. The Los Angeles, California wildfires are a prominent example of their potential severity. Modelling wildfire behaviour is crucial, yet complex, due to its dependence on multiple variables. Recent advancements in machine learning (ML) are being explored by researchers. However, physics-based ML models incorporating Computational Fluid Dynamics require extensive data, given the complex nature of wildfire behaviour and the inherent data volume requirements of many machine-learning approaches. Since material flammability heavily depends on weather conditions, collecting weather data is crucial to enhance understanding of fire behaviour.

Given my expertise in water resources, which frequently involves weather data, this project was a perfect match for both the host and me, complementing our skill sets. The project involved creating a weather data retrieval and visualization tool, coupled with a database management system for wildfire-related vegetation and flammability data. The data retrieval and visualization tool allow the download of important weather variables for a selected site by choosing the site, date, and time. It provides plots of conditions over the last seven days, along with a summary document. As the wildfire group collects data from various sites, managing this data long-term is challenging. A data management tool was developed for managing vegetation sampling data, and another for collating results of flammability testing conducted on the collected vegetation samples.

These tools aim to provide a foundation for improved assimilation of weather and wildfire-related date to better understand and model the complex behaviour of wildfires, via. an improved understanding of firstly, the link between weather and vegetation properties, and secondly, the subsequent link with vegetation flammability.

1. PROJECT OVERVIEW

1.1. Original Host Project Proposal

The proposed project specified development of a robust protocol and a suitable database for fire science experimental data. Researchers at the UoE and collaborating partners have existing datasets spanning multiple experimental scales, describing the flammability and fire behaviour of a variety of materials in the context of both fire safety in the built environment, and prediction of wildfire behaviour. These datasets are already utilized in efforts to develop improved modelling tools ranging from simple statistical models to more complex, detailed physics-based models (which incorporate Computational Fluid Dynamics).

However, there is significant potential to further utilize both existing and future experimental datasets, to support the development of physics-informed Machine Learning (ML) models, to predict the complex phenomena involved in fire behaviour. This is a novel and emerging area within the field of fire science & engineering, and this proposed project will therefore develop and define a novel, robust framework for preparing and storing relevant experimental datasets for use in physics informed ML development (training, validation & testing).

1.2. Project Plan

Wildfire behaviour is complex, as it is driven by a variety of factors including ecology, weather, physics, and human activity. For example, fire behaviour in a particular type of vegetation varies depending on moisture content, sample geometry, material properties, and environmental conditions. Predicting wildfires is difficult due to the involvement of many interdependent variables.

Recently, wildfire incidents have increased in severity and frequency in many regions due to global climate change (amongst other factors). Regional climate conditions exert a strong influence on the likelihood of fire outbreaks and the subsequent wildfire behaviour.Understanding the complex relationships between climate/weather, key vegetation properties (e.g. moisture content) and flammability requires the improvement of existing fuel models, often adapted from regions with highly contrasting vegetation types. One possible route to developing improved fuel models is to incorporate physics-informed Machine Learning (ML) models. However, these ML models rely heavily on high-quality experimental and vegetation sampling data.

In this project, to analyse the fire behaviour of a vegetation sample from a site, a Cone Calorimeter is used to characterise material flammability. The primary outputs include time to ignition, mass loss rate, and heat release rate. These results are influenced by vegetation properties (e.g. moisture content, sample geometry, material type) which are in turn affected by site conditions (e.g. weather and topography). By linking these flammability results with existing weather data - such as humidity, wind speed, precipitation, and temperature - we can build a more holistic view of fire behaviour. However, this complexity also complicates data preparation and storage, especially as the volume of data increases, posing challenges in handling big data effectively.

Given my background in weather science and big data analysis, the project provided a strong overlap with the host's expertise in fire science, and the specific project direction was shaped accordingly. It was particularly engaging to work on this project, especially considering recent wildfire events such as those in Los Angeles, California, in 2025, which were triggered by climate whiplash events - sudden shifts in climatic conditions over a short period. Since wildfires are closely linked to weather conditions, this connection provided a valuable perspective for understanding the complexity of wildfire behaviour.

Obtaining relevant data is often the most challenging part when building ML models for wildfires. I worked on retrieving key weather variables - such as precipitation, evaporation, evapotranspiration, and more - for three sampling sites: Drumbrae, Rullion Green Wood, and Barvick Burn Wood. These sites are owned by The University of Edinburgh as part of the Forest & Peatlands Programme (https://sustainability.ed.ac.uk/operations/forest-peatland) and provide a Living Lab for understanding weather-linked vegetation response in key Scottish vegetation types. The data were obtained from two sources: most variables were downloaded from the ERA5 Single Levels Reanalysis dataset through the Copernicus Climate Data Store (https://cds.climate.copernicus.eu/datasets/reanalysis-era5-single-levels), while soil moisture data were retrieved separately from the Surface Soil Moisture dataset provided by the Copernicus Land Monitoring Service (https://land.copernicus.eu/en/products/soil-moisture). Vegetation sampling is underway at one of these sites (Drumbrae) and will soon be expanded to the other sites. The collected samples are then characterised using a Cone Calorimeter to evaluate their flammability.

The primary objective of our project was to develop a robust framework for preparing and storing weather variables and experimental datasets in fire science, aimed at supporting the development of physics-informed machine learning (ML) models.

Tasks assigned:

1. Collect the envionmental conditions of the collection sites
2. Understanding the processes involved in testing the sample
3. Analyzing the output results of the cone calorimeter test
4. Developing a robust framework to prepare and store these pretest datasets and posttest datasets

2. ACTIVITIES PLAN

Table 1 – Summary of Finalized Tasks and Their Corresponding Detailed Actions

Task	Action
Project set-up	Familiarised myself with existing wildfire behaviour in order to gain a good understanding of how weather data interacts with wildfires.
Collecting Environmental Data	In this step, I aimed to narrow down the variables we should focus on, considering that many environmental variables can be redundant. The goal was to identify and focus only on the variables most relevant to understanding complex wildfire behaviour.
Understanding sample testing process	This part connected my existing skills in weather data to the wildfire domain, where I gained hands-on experience in how to conduct sample testing for vegetation samples collected by the Wildfire Group.
Analysing the Cone Calorimeter Test Results	The results obtained from the cone calorimeter can be difficult for a new person to interpret. This step involved analysing what the results actually mean and how we can extract useful insights from them.
Developing framework for the Environmental and experimental datasets	This involved writing a python script for a data retrieval and visualization tool for a selected site, based on the date and time specified by the user. The tool fetches environmental data for the 7 days prior to the selected date, providing context on pre-existing conditions through plots and summary statistics. Additionally, tools were developed for the wildfire group to manage sampling data and to test and visualize the sampled data. These tools present the results in a simplified format, making them easier to interpret and understand.
Code Clean-up	This step involved debugging the code and preparing it with proper instructions, so that researchers in the Wildfire Group can use it as a go-to tool for data retrieval. The tool allows users to assess conditions at any site by simply entering the date and time. A well-documented notebook was created, with clear instructions to account for potential complications that might arise.
Project Report	Prepared a comprehensive project report.

3. OUTCOMES

3.1. Weather Retrieval and visualization tool

Weather influences wildfire behaviour both indirectly and directly. Indirectly, it affects the moisture content of vegetation, depending on factors such as particle size, ground contact, the season, and short-term weather conditions like solar radiation, precipitation, humidity, and air temperature. Directly, weather impacts wildfire behaviour through for example the effect of wind on flame spread. This can be understood in a detailed way by referring to the wildland fire behaviour triangle which comprises three environmental components: fuel, weather and topography.

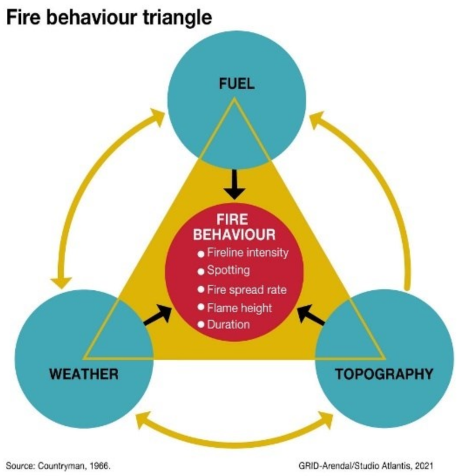


Figure 1 The wildland fire behaviour triangle comprises three environmental components: fuel, weather and topography. Source: GRID-Arendal, https://www.grida.no/resources/15585

There are many potentially relevant weather variables to consider, but our aim was to narrow them down to the most important ones. The logic behind eliminating variables was based on their significance for future applications in wildfire studies. Only the variables deemed highly relevant to wildfire behaviour were selected. However, a few variables - such as soil temperature levels 1 to 4 - were included to leave room for future wildfire studies, in case upcoming models incorporate them.

The tool was designed to be flexible - users can easily add more sites, include or remove weather variables, or focus on historical data beyond the last 7 days simply by updating the site list, adjusting variables, and changing the requested date range. This design allows for easy addition or modification of variables in the future.

The variables selected for download were:

- 10-metre U wind component
- 10-metre V wind component

- 2-metre dewpoint temperature
- 2-metre temperature
- total precipitation
- surface direct short-wave radiation (clear sky)
- evaporation
- potential evaporation
- soil temperature level 1
- soil temperature level 2
- soil temperature level 3
- soil temperature level 4
- leaf area index (high vegetation)
- leaf area index (low vegetation)
- soil moisture.

Note: Detailed description of each of these variables is provided in appendix A.

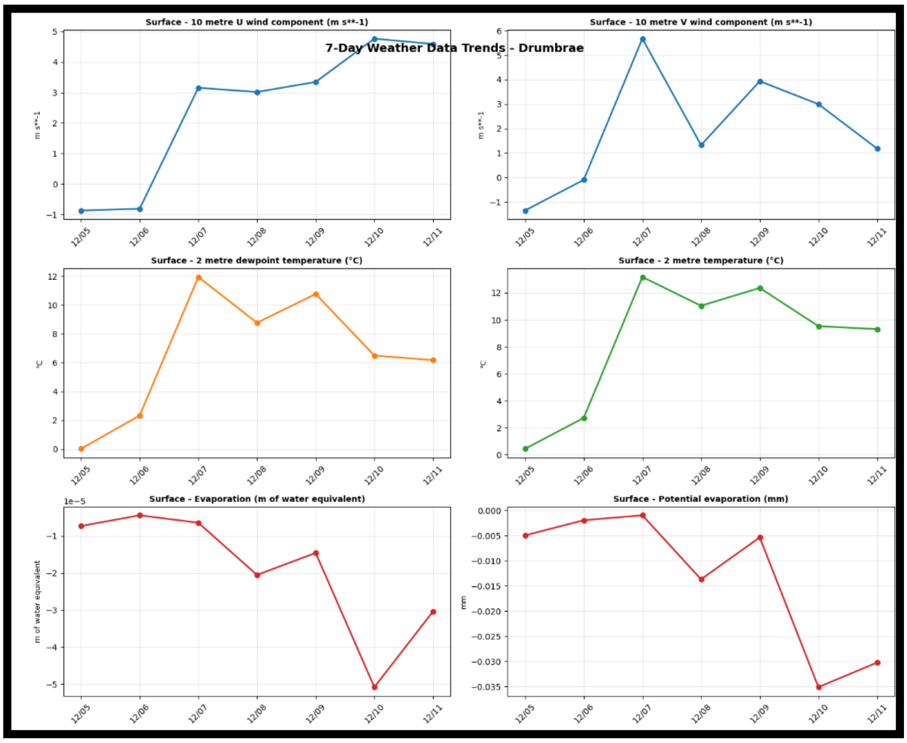
All data, except soil moisture, were downloaded using the ERA5 Single Levels Reanalysis dataset(https://cds.climate.copernicus.eu/datasets/reanalysis-era5-single-levels?tab=download). Soil moisture data were obtained separately, and was obtained from the Surface Soil Moisture dataset provided by the Copernicus Land Monitoring Service (https://land.copernicus.eu/en/products/soil-moisture).

The tool was developed using a python script, and its functionality can be demonstrated using the example of the Drumbrae site:

1. The user simply selects the site they are interested in.
2. They then enter the date and time of interest.
3. The tool retrieves the relevant data from the data sources for the selected date, along with data from the previous 7 days. This helps in understanding how the conditions on the selected date compare to those of the preceding days, and will allow greater investigation of the effect of preceding weather conditions on vegetation condition.

```
=== Combined Environmental Data Analysis System ===
This system retrieves both soil moisture and weather data for comprehensive analysis.

Please enter the site number you are interested in:
 1. Rullion Green Wood
 2. Drumbrae
 3. Barvick Burn Wood
 2
Please enter the date you are interested in (in YYYY/MM/DD format):  2016/12/11
Please enter the time of the day you are interested in (in 24hr format hh:mm):  13:00

=== Processing data for Drumbrae ===
Target date: 2016/12/11, Time: 13:00
Date range: 2016/12/05 to 2016/12/11

 Fetching soil moisture data...
Found 7 soil moisture files
 Successfully processed 7 soil moisture data points

 Fetching weather data...

=== Downloading 7 Days of Weather Data ===
 Downloading weather data for 2016/12/05...
```

4. Once retrieval finishes, each variable can be visualized as a time series plot showing how values at the selected time (e.g., 13:00) have changed over the past 7 days.



5. Finally, a summary report is generated, which includes the data for the selected date along with the mean, minimum, and maximum values from the past 7 days.

7-DAY SUMMARY STATISTICS

Variable	Mean	Min	Max	Std	Value on 2016/12/11
Surface - 10 metre U wind component (m s**-1)	2.45	-0.87	4.77	2.35	4.59
Surface - 10 metre V wind component (m s**-1)	1.95	-1.35	5.67	2.41	1.18
Surface - 2 metre dewpoint temperature (°C)	6.64	0.02	11.94	4.32	6.17
Surface - 2 metre temperature (°C)	8.37	0.45	13.17	4.88	9.31
Surface - Evaporation (m of water equivalent)	-0.00	-0.00	-0.00	0.00	-0.00
Surface - Potential evaporation (mm)	-0.01	-0.04	-0.00	0.01	-0.03
Surface - Surface direct short-wave radiation, clear sky (J m**-2)	340866.55	320686.62	389455.50	22921.15	324512.44
Surface - Total precipitation (mm)	0.02	0.00	0.06	0.02	0.00
Land - Leaf area index, high vegetation (m**2 m**-2)	2.18	2.17	2.19	0.01	2.17
Land - Leaf area index, low vegetation (m**2 m**-2)	2.44	2.42	2.46	0.01	2.42
Land - Soil temperature level 1 (K)	278.32	272.86	281.52	3.69	279.36
Land - Soil temperature level 2 (K)	277.43	273.89	279.51	2.53	278.67
Land - Soil temperature level 3 (K)	277.26	276.49	278.35	0.76	278.35
Land - Soil temperature level 4 (K)	280.77	280.56	281.04	0.18	280.56

Summary statistics saved to: weather_summary_2_20161211_1200.csv

3.2. Sampling data management tool

Since, the wildfire group collects a lot of samples for testing and managing this data in long term becomes a tedious task. So as to deal with that and extract the important data which is of concern for the researchers in wildfire group this tool was developed.

Steps involved are:

1. User just needs to enter the file they are interested in.
2. Then select the date/sheet they are interested in
3. This gives them the resulting data of mean, standard deviation, standard error values for the Avg Fine Live, Avg Fine Dead, Avg Coarse and Avg Litter fuel types (each of which describes a different fuel strata for common Scottish shrub fuels).

```
################################################################################
      Welcome to the data extraction of Vegetation Sampling Data
################################################################################
['Vegetation_Moisture_Sampling 1.xlsx']
Select file you are interested in:
1: Vegetation_Moisture_Sampling 1.xlsx

Enter the number of file you are interested in 1

Sheet Names found inside the selected file:
['17_09_2024_Drumbrae', '30_10_2024_Drumbrae', '27_02_2025_Drumbrae', '07_04_2025_Drumbrae', '19_05_2025_Drumbrae']
1:17_09_2024_Drumbrae
2:30_10_2024_Drumbrae
3:27_02_2025_Drumbrae
4:07_04_2025_Drumbrae
5:19_05_2025_Drumbrae

Enter the file number you are interested in: 5
################################################################################
 Mean, Standard Deviation(SD), Standard Error(SE) values for the Avg Fine Live, Avg Fine Dead, Avg Coarse and Avg Litter:
################################################################################

Avg Fine Live values:
Mean (%): 22.675
SD: 3.034
SE: 0.433
################################################################################

Avg Fine Dead values:
Mean (%): 9.84
SD: 1.953
SE: 0.279
################################################################################

Avg. Coarse values:
Mean (%): 30.424
SD: 6.508
SE: 0.93
################################################################################

Avg Litter values:
Mean (%): 5.687
SD: 2.26
SE: 0.323
################################################################################
```

3.3. Cone Calorimeter Testing

Before developing the next tool, it was important to understand how the testing process works so that I could better interpret and break down the complex output. To do this, I had the opportunity to access the Edinburgh Fire Research Centre Laboratory and perform Cone Calorimeter testing on collected samples.

Why is this test performed?

The main objective of the Cone Calorimeter test is to determine the flammability of a material. The output includes measurements of oxygen depletion in the exhaust gasses during combustion, as well as key plots such as heat release rate vs. time and mass vs. time.

The Cone Calorimeter standard method, defined in ISO 5660-1:2015, is a standardized procedure for evaluating the fire performance of materials by measuring heat release, smoke production, and mass loss rates under controlled radiant heat exposure.

Figure 2 Wildland Fuel Sample

Figure 3 Cone Calorimeter

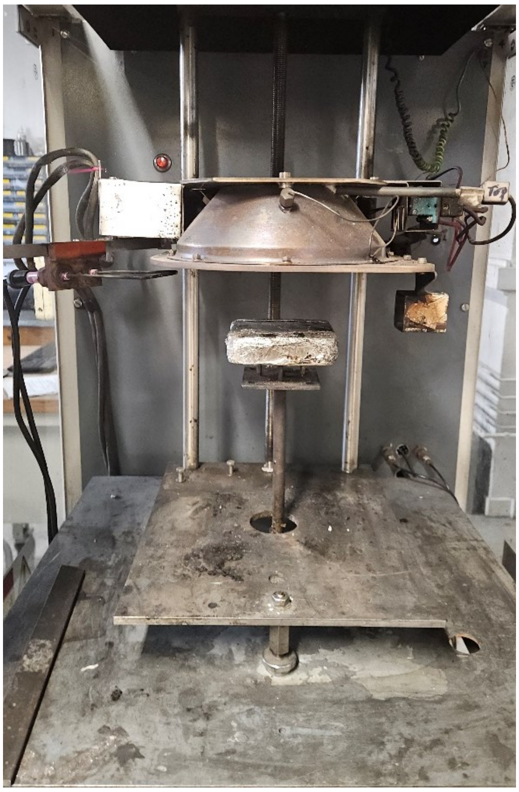


Figure 4 Testing area of a Cone Calorimeter

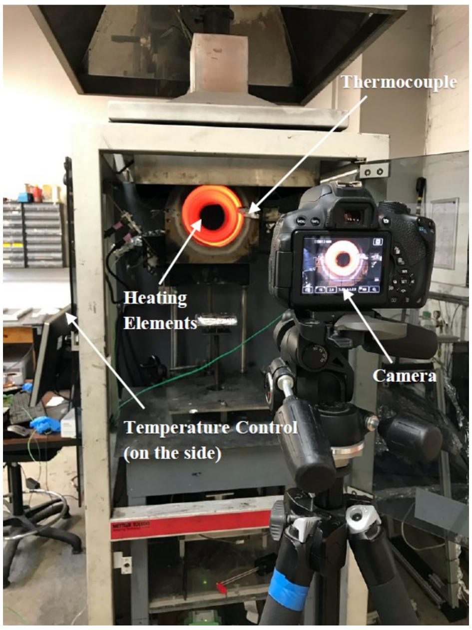


Figure 5 Cone Radiant Heater

We have included some snapshots to give a rough idea of how this testing is conducted:

1. Placing the sample inside the testing chamber.
2. Slowly heating the coil to radiate heat onto the sample.
3. The sample begins to emit smoke as pyrolysis occurs.
4. The flammable gases released during pyrolysis are ignited using a spark, which acts an ignition pilot.
5. The sample burns rapidly, releasing heat, and then enters a decay phase.

Figure 6 Placing the sample into the cone calorimeter

Figure 7 Visual observation of flaming combustion in cone calorimeter test

Figure 8 Decreased flaming combustion visually observed as combustion progresses.

3.4. Testing Data Management Tool

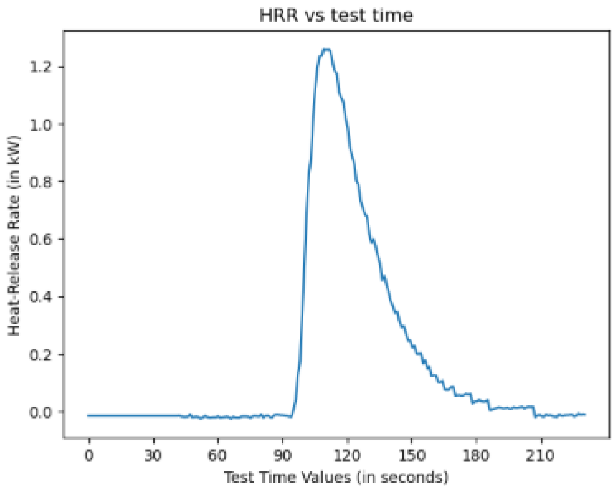
Once the testing is complete, the output results are recorded in an Excel file (.xls or .cs), which may be difficult for a new user to interpret. Therefore, it became necessary to extract the key data and visualize it using plots to make the results more understandable. Additionally, managing individual sample data over time can become challenging, so a tool was developed to both extract and organize the test results efficiently.

Below is an example of how the test results appear in the Excel sheet.

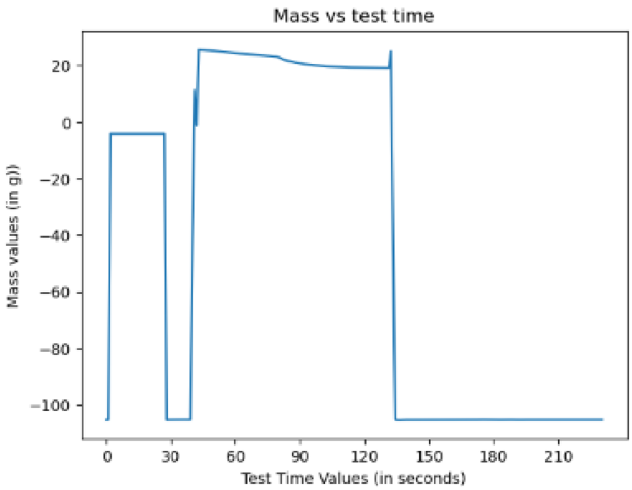
test_time (s)	mass (g)	conc_O2 (%)	conc_CO (ppm)	conc_CO2 (%)	Heat Release Rate (kW)	ignition_occur	flameout_occur
0.00	-105.21	21.00	0.79	0.02	-0.01	0	0
1.01	-105.21	21.00	0.74	0.02	-0.01	0	0
2.00	-4.15	21.00	0.82	0.02	-0.01	0	0
2.99	-4.15	21.00	0.76	0.02	-0.01	0	0
4.01	-4.14	21.00	0.78	0.02	-0.01	0	0
5.00	-4.14	21.00	0.77	0.02	-0.01	0	0
6.01	-4.15	21.00	0.76	0.02	-0.01	0	0
7.01	-4.14	21.00	0.51	0.02	-0.01	0	0
8.02	-4.12	21.00	0.52	0.02	-0.01	0	0
9.04	-4.12	21.00	0.55	0.02	-0.01	0	0
10.04	-4.15	21.00	0.55	0.02	-0.01	0	0
11.06	-4.15	20.99	0.50	0.02	-0.01	0	0
12.06	-4.15	20.99	0.54	0.02	-0.01	0	0
13.07	-4.15	20.99	0.49	0.02	-0.01	0	0
14.06	-4.14	20.99	0.53	0.02	-0.01	0	0
15.06	-4.13	20.99	0.55	0.02	-0.01	0	0
16.06	-4.13	20.99	0.53	0.02	-0.01	0	0
17.07	-4.15	20.99	0.52	0.02	-0.01	0	0
18.08	-4.15	20.99	0.50	0.02	-0.01	0	0
19.08	-4.16	20.99	0.54	0.02	-0.01	0	0
20.08	-4.16	20.99	0.49	0.02	-0.01	0	0
21.09	-4.16	20.99	0.57	0.02	-0.01	0	0
22.09	-4.16	20.99	0.53	0.02	-0.01	0	0
23.09	-4.17	20.99	0.53	0.02	-0.01	0	0
24.09	-4.15	20.99	0.50	0.02	-0.01	0	0
25.10	-4.14	20.99	0.48	0.02	-0.01	0	0
26.09	-4.15	20.99	0.56	0.02	-0.01	0	0
27.10	-4.15	20.99	0.56	0.02	-0.01	0	0
28.09	-105.25	20.99	0.55	0.02	-0.01	0	0
29.10	-105.19	20.99	0.52	0.02	-0.01	0	0
30.09	-105.18	20.99	0.50	0.02	-0.01	0	0
31.11	-105.18	21.00	0.53	0.02	-0.01	0	0
32.11	-105.17	21.00	0.55	0.02	-0.01	0	0
33.11	-105.16	21.00	0.54	0.02	-0.01	0	0
34.11	-105.16	21.00	0.49	0.02	-0.01	0	0

The following shows the format of the data extracted by the tool:

```
################################################################################
Welcome to the data extraction of Cone Calorimeter testing results from the files
################################################################################
['Wildland_Fuel_Example_Output.xlsx']
Select file you are interested in:
1: Wildland_Fuel_Example_Output.xlsx

Please enter the file number you are interested in: 1

Sheet Names found inside the selected file:
['Sheet1']
1:Sheet1

Please enter the file number you are interested in: 1
################################################################################
Maximum Heat Release Rate in kW is: 1.2604590637347355
################################################################################
HRR vs Test Time values plot:
```




```
################################################################################
Mass vs Test Time values plot:
```



Additional post-processing could be included by future users if desired e.g. truncating the data based on time of sample insertion and removal would result in a simpler mass plot. Finally, a notebook was created that includes details about the tools and important points to consider before running them. This notebook will serve as a clear guidance document for future users, allowing the tool to be used in upcoming student projects.

We are planning to collaborate in the near future to further develop this project by incorporating terrain and high-resolution aerial photography data using Digimap, which is accessible through the University. As we saw in the fire behaviour triangle, we have already addressed two components - fuel and weather. Now, the third component, topography, needs to be considered to make wildfire modelling more accurate by integrating these complex aspects together.

3.5. Dissemination & Future Use

The developed tool is also available for immediate use within ongoing and planned research projects, including an upcoming MSc project which will generate additional data for inclusion in this database. This will be supported by the documentation and best practice guidance produced in this project and through a 1-2-1 hand-over session.

There is also the potential to integrate this tool within teaching activities particularly to support the teaching of fieldwork skills within existing courses in the School of Engineering. We also plan to present the developed tool and data management system to the Forest & Peatlands Learning & Teaching Committee, to demonstrate its utility as a tool to support the use of the UoE (and potentially partner) sites as Living Labs for understanding vegetation flammability at a site-specific scale.

4. CLOSING REMARKS

As shown in the wildland fire behaviour triangle, the key factors influencing wildfire behaviour are fuel, weather, and topography. We have developed a tool to retrieve important weather variables that can be directly used in modelling fire behaviour. Since the wildfire group is already managing sampling data, we contributed by creating a couple of small tools to help them manage their data more efficiently.

However, wildfire behaviour is quite complex, involving many other factors such as topography and fuel characteristics. Having access to both weather data and fuel sampling data allows the wildfire group to potentially link these variables and identify important signals to better understand and model fire behaviour.

It was a great experience working with the wildfire team on this project, leading to several fruitful discussions. This work complements both our areas well - water resources and wildfire science - making it a perfect collaboration. We definitely plan to take this project further, aiming to analyse UK wildfires and explore whether droughts and heat extremes have a direct connection to wildfire occurrences. Since my research focuses primarily on droughts and heat extremes, this collaboration could help answer questions about how these factors behave and whether there are detectable signals linking them to wildfires.

5. APPENDIX A

Variables Description:

All the variables description are taken up from European Centre for Medium-Range Weather Forecasts parameter database (https://codes.ecmwf.int/grib/param-db/)

10m u-component of wind: " This parameter is the eastward component of the 10m wind. It is the horizontal speed of air moving towards the east, at a height of ten metres above the surface of the Earth, in metres per second."

10m v-component of wind: " This parameter is the northward component of the 10m wind. It is the horizontal speed of air moving towards the north, at a height of ten metres above the surface of the Earth, in metres per second."

2m dewpoint temperature: " This parameter is the temperature to which the air, at 2 metres above the surface of the Earth, would have to be cooled for saturation to occur. It is a measure of the humidity of the air."

2m temperature: " This parameter is the temperature of air at 2m above the surface of land, sea or in-land waters. 2m temperature is calculated by interpolating between the lowest model level and the Earth's surface."

Total precipitation: " This parameter is the accumulated liquid and frozen water, comprising rain and snow, that falls to the Earth's surface. It is the sum of large-scale precipitation and convective precipitation."

Clear sky direct solar radiation at surface: " This parameter is the amount of solar (shortwave) radiation reaching the surface of the Earth (both direct and diffuse) minus the amount reflected by the Earth's surface, assuming clear-sky (cloudless) conditions."

Evaporation: " This parameter is the accumulated amount of water that has evaporated from the Earth's surface, including a simplified representation of transpiration (from vegetation), into vapour in the air above."

Potential evaporation: " This parameter is a measure of the extent to which near-surface atmospheric conditions are conducive to the process of evaporation."

Soil temperature level 1: " Temperature of the soil in layer 1 (0-7cm below surface). Soil temperature is set at the middle of each layer, and heat transfer is calculated at the interfaces between them."

Soil temperature level 2: " Temperature of the soil in layer 2 (7-28cm below surface). Soil temperature is set at the middle of each layer, and heat transfer is calculated at the interfaces between them."

Soil temperature level 3: " Temperature of the soil in layer 3 (28-100cm below surface). Soil temperature is set at the middle of each layer, and heat transfer is calculated at the interfaces between them."

Soil temperature level 4: " Temperature of the soil in layer 4 (100-289cm below surface). Soil temperature is set at the middle of each layer, and heat transfer is calculated at the interfaces between them."

Leaf area index, high vegetation: " This parameter is the surface area of one side of all the leaves found over an area of land for vegetation classified as 'high'. This parameter has a value of 0 over bare ground or where there are no leaves."

Leaf area index, low vegetation: " This parameter is the surface area of one side of all the leaves found over an area of land for vegetation classified as 'low'. This parameter has a value of 0 over bare ground or where there are no leaves."

6. REFERENCES

1. Bifulco, A., Climaco, I., Casciello, A., Passaro, J., Battegazzore, D., Nebbioso, V., Russo, P., Imparato, C., Aronne, A. and Malucelli, G., 2025. Prediction and validation of fire parameters for a self-extinguishing and smoke suppressant electrospun PVP-based multilayer material through machine learning models. Journal of Materials Science, 60(2), pp.1019-1040.
2. Finney, M.A., McAllister, S.S., Forthofer, J.M. and Grumstrup, T.P., 2021. Wildland fire behaviour: dynamics, principles and processes. CSIRO publishing.
3. ISO. (2015). ISO 5660-1:2015 Reaction-to-fire tests — Heat release, smoke production and mass loss rate — Part 1: Heat release rate (cone calorimeter method). Geneva: ISO. Available at: https://www.iso.org/standard/57957.html
4. Valayanad, S.P. and Arnold, L., 2024, November. AI-Based Material Parameter Prediction from Cone Calorimeter Measurements. In Journal of Physics: Conference Series (Vol. 2885, No. 1, p. 012013). IOP Publishing.