

FireInSite: an Accessible, Integrated Fire Behaviour Prediction System for the UK and Ireland

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FireInSite: an Accessible, Integrated Fire Behaviour Prediction System for the UK and Ireland

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Abstract

Accessible tools to support wildfire management are lacking for humid temperate regions. We developed FireInSite as a user-oriented system for predicting fire behaviour for major fire-prone fuels at any location in the UK and Ireland. Extensive fuel moisture, flammability, and seasonally varying energy content data underpin FireInSite's integrated fuel moisture, heat content, and fuel modules. The user-friendly interface requires no user input to generate fire behaviour predictions, other than selecting a location of interest or using the automatic geolocated selection. It does so by characterising the state of the fuels of interest at any point in the season in respect to a location's climatology and weather as novel modules and then directing the relationships between these modules into a fire behaviour prediction model based on the Rothermel family of equations. As well as hourly forecasts, hindcasts of fire behaviour are also available back to 1970 and weather and fuel moisture forecasts can be compared to historical conditions. FireInSite therefore enables assessment of fire risk, effects of fuel load reduction, or planning for fire prevention and suppression. FireInSite has been used by Fire and Rescue Services and land managers in the UK and Ireland since 2025, and community response and validation have demonstrated the skill of FireInSite as a decision support tool. FireInSite's capabilities therefore provide previously lacking support for the UK, Ireland, and comparable

humid temperate regions, enabling them to better prepare for and mitigate their accelerating wildfire risk.

1. Introduction

Wildfire risk is increasing in most regions across the globe, driven by shifts in climate and fuel availability (Jones et al., 2022; Yang et al., 2026). This includes humid temperate regions such as the UK and Ireland where particularly large and impactful wildfires have occurred in recent years (Perry et al., 2022; Miller et al., 2024; Iverson et al., 2025b). To anticipate and manage wildfires, as well as planned vegetation fires such as prescribed burns aimed at reducing vegetation fuel or at ecosystem restoration, tools to predict fire behaviour have been an essential resource for decades. They are used to predict vegetation fire behaviour parameters such as probability of ignition, flame length, rate of spread, and fireline intensity and are applied in training; operational decision making in terms of fire prevention, fire suppression, or the use of prescribed burning; and for research for mitigation, planning, and response to actual and simulated fires. They range from relatively simple predictors such as hand-held Kestrel fire weather meters (Kestrel, 2016) used widely by firefighters; to more complex point-based models with region-specific fuel models such as *BehavePlus* (Andrews, 2014) often used by researchers; and commercial prediction models like Wildfire Analyst (Monedero et al., 2019), which are oriented towards operational use and also offer fire spread predictions and scenario analyses. In many wildfire-prone countries such as Australia, Canada, USA, and in some Mediterranean countries, fire behaviour models have been developed specifically for national use or models have been tailored for country specific conditions (Sullivan, 2009; Cardil et al., 2021). The United Kingdom, Ireland, and many other humid temperate regions, however, lack a tailored fire behaviour model and prediction tool despite the recent and predicted further increase in vegetation fire risk. For example, the area burned by vegetation fires in the UK in 2025, as estimated via satellite observations, was by far the largest since systematic recording began in 2004 (Fernando et al., 2026).

With this growing risk comes the need for operational fire behaviour prediction tools to support decision-making needs for land managers, Fire and Rescue Services, and other stakeholders involved in wildfire preparedness and response. However, there have been several challenges hindering their development and application in the UK, Ireland, and comparable humid temperate regions. The development of fire behaviour prediction systems has historically

centred on more fire-prone regions like Australia, Canada, and the USA (Andrews, 2014; Monedero et al., 2019). As a result, existing operational systems and fuel models have been designed around the fire regime characteristics of these regions. In contrast, as an emerging risk in humid temperate regions, empirical fuel and fire behaviour datasets are limited, and there is a distinct lack of specific fuel models that capture the dynamics of fuels in these ecosystems (Stoof et al., 2024; Little et al., 2025). Critically, a key challenge is that fire regimes in humid temperate regions are strongly coupled to seasonal variability in live fuel flammability linked to the phenological cycle of vegetation growth (Nikonovas et al., 2024; Belcher et al., 2025). These phenological controls can produce pronounced intra-annual variation in fuel moisture and combustibility, meaning that fire potential may change rapidly through the year and may not be well represented by static fuel descriptions commonly used in many existing models.

At the national UK level, Met Office has developed a service known as the Fire Severity Index (FSI, now hosted by (Natural England, 2026)), which is essentially a fire weather predictor based on the Canadian Fire Weather Index (Van Wagner, 1987). It uses wind speed, temperature, time of year, and rainfall to produce a 'Fire Severity Index' indicating how 'severe' a fire could become if one were to start (Natural England, 2026). Operationally, landowners and Fire and Rescue Services also consult EFFIS (European Forest Fire Information System, 2026), which includes, via its 'current situation viewer', the ability to consult a range of outputs from different fire danger rating indices with the highest resolution being 8 km². However, neither of these services provide specific fire behaviour information, are tailored for different fuel types, or operate at high spatial resolution. Whilst useful for regional level risk awareness and, in the case of the UK's FSI, used for triggering fire prevention restrictions on access land mapped under the Countryside and Rights of Way Act (2000), these services are therefore of limited use in decision-making at local fuel, terrain, and weather conditions for land managers, Fire and Rescue Services, and other stakeholders involved in wildfire preparedness and response.

Another challenge common to many existing fire behaviour prediction tools is that they are not particularly accessible to the wide range of potential users who may benefit from them. Potential users often need to consult multiple data sources and websites to obtain the meteorological, fuel, and landscape information required to run models, be familiar with handling geospatial data, and select appropriate input parameters requiring expert judgement. This fragmented workflow can create significant barriers for operational users who require rapid, clear, and integrated information to support time-sensitive decisions.

There is a critical need for predictive tools to support decision making for fire managers that are grounded in the specific fuels of their regions. To meet this need we addressed the challenges outlined above and developed *FireInSite*, the UK's first fire behaviour prediction system, which is freely accessible at <https://www.fireinsite.org/>. In this manuscript we present the novel developments of *FireInSite* to date, which overcome some of the major challenges of predicting fire behaviour in humid temperate regions experiencing increasing wildfire risk. Its novelty lies in combining (i) a user-friendly interface that requires no further user input to derive predictions for a particular type of fuel and location, (ii) the new data from common fire-prone fuels in the UK and Ireland and their live and dead moisture content as well as phenologically-driven heat content, and (iii) automatic retrieval of current weather and weather forecasts from several sources and relevant terrain characteristics (slope and aspect). This manuscript forms a comprehensive user manual for *FireInSite*, detailing *FireInSite*'s structure; predictions' relationship to existing fire behaviour models; collection of extensive underlying data on fuels, fuel moisture content (FMC), flammability, and links to phenology; retrieval and incorporation of secondary data; model development; validation; and future development opportunities.

2. *FireInSite* Structure and Predictions

2.1 *FireInSite*'s Relationship to Existing Fire Behaviour Models

FireInSite 1.0 draws together a series of equations and algorithms, combining a set of models in one user-friendly, free to use, web-based interface or 'system'. *FireInSite* 1.0 is at present predominantly focussed on modelling fire behaviour in UK surface fuels, where the majority of fire-prone ecosystems in the UK are currently shrub and grass dominated and true crown fires are rare. *FireInSite* predicts surface rate of fire spread, flame length, and fireline intensity with the primary aim to be operationally useful to Fire and Rescue Services and land managers. These predictions are made using the Rothermel (1972) surface fire spread model including minor adjustments from Albini (1976), which calculates the rate of spread of fire in surface fuels. Flame length and fireline intensity predictions are based on the models developed by Byram (1959) via the Albini (1976) method for using those models with the Rothermel model. The equations, algorithms, and their interdependencies are for the majority taken from Andrews (2018), such that *FireInSite* shares large commonality with Missoula Fire Sciences Laboratories Behave family of modelling systems. However, it includes a range of novel developments, underlain by four years of intensive data collection that describe temperate UK fire-prone fuel types, their fuel

moisture, and a range of interdependencies with weather and phenology. Moreover, the front interface for FireInSite (Section 3) requires minimal input from the user; the user need only select a location on a map and then FireInSite sources all the relevant data it requires to make fire behaviour predictions for UK fuel types. FireInSite provides the user with a range of information (Table 1) upon selecting a location or geolocating themselves on the map interface.

Table 1. Summary of FireInSite outputs provided.

Information Provided/Predicted	Notes
Five-day weather forecast presented hourly; relative humidity (%), temperature (°C), rain (mm), wind speed (kmh ⁻¹), wind gusts (kmh ⁻¹), wind direction, vapour pressure deficit (VPD)	Three weather models to choose from a) UK Met Office 2 km resolution for UK and 10 km for global model b) ECMWF IFS, 9 km degree global model c) ICON, German weather service (DWD) ICON model with 2 km (central Europe), 7 km (Europe), and 11 km (global) resolution Historical weather is retrieved from ERA5-land and ERA5 reanalysis datasets
Dead fuel moisture (for 1 hour/ fine fuels)	Three moisture models to choose from a) FireInSite dead fuel moisture model, developed specifically for the UK, based on field collected data linked to phenological and weather drivers (Section 5.2) b) Simple FPMC, the simple Nelson dead fuel moisture model (Jolly et al., 2016) c) Fosberg, dead fuel moisture as calculated using the Fosberg model (Fosberg et al., 1971)
Probability of Ignition	The probability that a firebrand (or spark) will cause an ignition. Depends on dead 1 hour fuel moisture, temperature, and fuel shading. The equation used to calculate the probability of ignition is that developed by Schroeder (1969).
Flame Length (m)	Surface fire flame length of a spreading surface fire within the flaming front is measured from midway in the active flaming combustion zone to the average tip of the flames. According to Rothermel (1991), "flame length is an elusive parameter that exists in the eye of the beholder. It is a poor quantity to use in a scientific or engineering sense, but it is so readily apparent to fireline personnel and so readily conveys a sense of fire intensity that it is worth featuring as a primary fire variable." Both surface fireline intensity and surface fire flame length are related to the heat felt by a person standing next to the flames. Flame length is calculated from fireline intensity, which is a function of surface fire rate of spread and heat per unit area (Byram (1959) and Albini (1976)).
Fireline intensity (MJm ⁻¹ s ⁻¹)	Surface fireline intensity is the heat energy release per unit time from a one-foot (one-meter) wide section of the fuel bed extending from the front to the rear of the flaming zone of a surface fire. Surface fireline intensity is a function of surface fire rate of spread and surface fire heat per unit area. Both surface fireline intensity and surface fire flame length are related to the heat felt by a person standing next to the flames. Surface fireline intensity is directly related to and is used in the calculation of flame length (see Byram (1959) and Albini (1976)).
Heat per Unit Area (MJm ⁻²)	The total heat released per unit area, a product of the reaction intensity and the time that the area is in the flaming zone, as indicated by the residence time (see Andrews (2018)).
Crown fire transition height (m)	Canopy base height at which a surface fire is likely to transition to a crown fire. This is the height at which the surface fire intensity is equal to critical fire intensity sufficient to ignite the crown fuels. Built specifically for FireInSite (Section 5.4).
Historic Mode	Ability to explore historical conditions by calling request data for any given location for a past date.

2.2 Novel Developments in FireInSite

Whilst the basic equations and connecting algorithms in FireInSite 1.0 are those outlined in Andrews (2018), it includes a range of novel developments to make realistic predictions for the UK's fire prone ecosystems, underlain by four years of intensive data collection. These developments include fuel models, phenologically-driven live and dead fuel moisture prediction systems, and phenologically-driven heat content systems specific to the UK's fire-prone species. Moreover, to meet our aim of providing a simple web-based interface that extracts all required data based on location, FireInSite required a set of automatically collated inputs to be developed and connected to reflect the input parameters for the fire behaviour models: 1) automatic retrieval of current weather and weather forecasts from several sources; 2) auto-retrieval of slope and aspect information; 3) auto-calculation of dead and live fuel moisture; and 4) auto-reading of heat content from month for each of its inbuilt custom fuel models according to phenology (Belcher et al., 2025).

2.3 FireInSite Structure

The FireInSite fire behaviour prediction system is built to automatically extract key input variables (detailed in Section 4) for a defined location and feed these into the embedded fuel moisture and heat content system to predict fire behaviour characteristics for FireInSite's fuel models (Fig 1). By default, input variables will be extracted from the user's IP geolocation, but a different location can then be manually selected. Topographic information is extracted and input into the systems for predicting fuel moisture and fire behaviour. Additionally, weather forecast information and time of year are automatically extracted and used to predict live and dead fuel moisture for FireInSite's fuel models. Time of year is also used to determine which heat content system to use for each fuel model. Finally, topographic information and predicted fuel moisture contents are used to predict aspects of fire behaviour for each phenologically-adjusted fuel model.

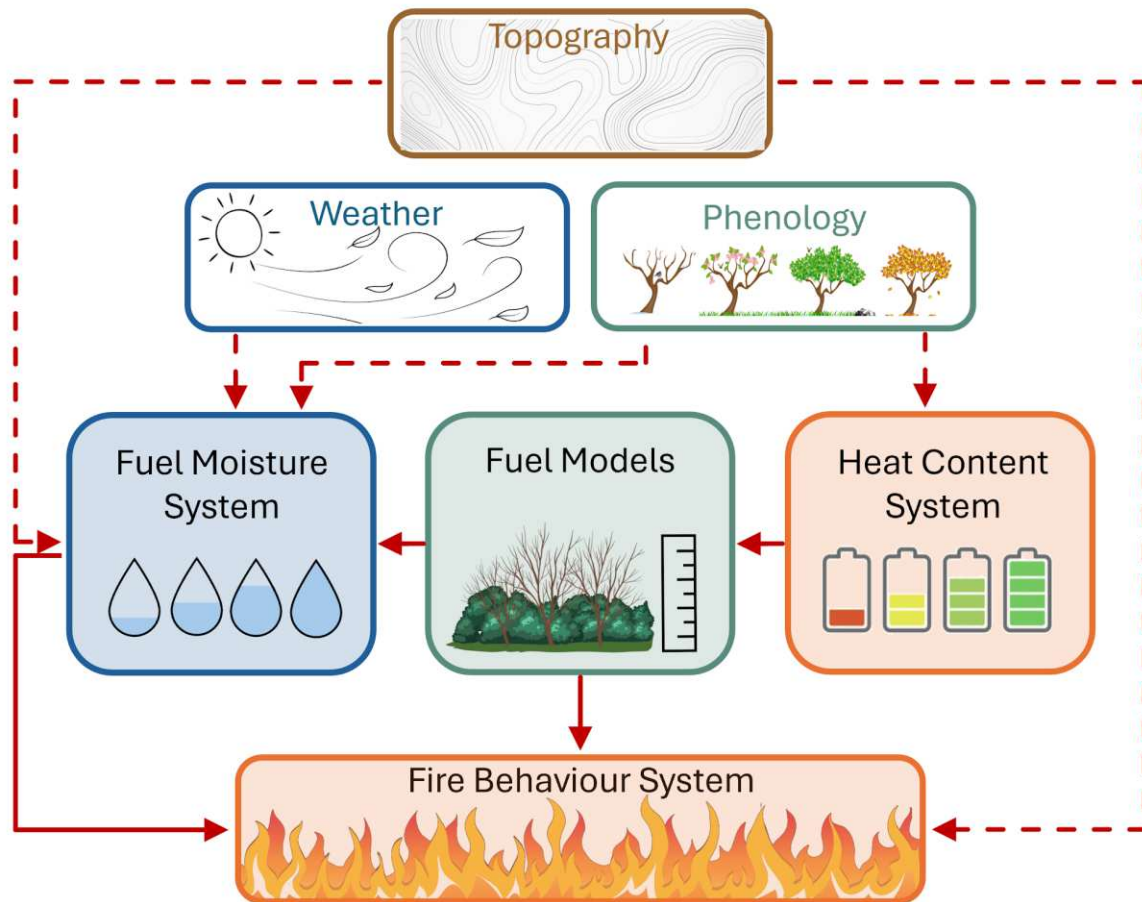


Figure 1. Conceptual diagram of FireInSite fire behaviour prediction system structure and inputs. Dashed arrows indicate automated extraction of data from the user's location, while solid arrows show data embedded in FireInSite.

3. Designing The FireInSite 1.0 Interface

Comparable fire behaviour prediction platforms to FireInSite require users to source their own data inputs. This requires users to have access to the different geospatial information needed in the correct format for the platform and the knowledge on how to implement the data to produce predictions. Even before predictions can be accessed, there are a lot of decisions that users must make to ensure predictions are representative of their environments, such as inputting sensible dead and live fuel moisture contents. We designed the FireInSite 1.0 web interface around non-specialist user needs, to create a simple, user-friendly application that removes barriers to predicting fire behaviour that exist in current prediction systems. Upon loading FireInSite, the user is immediately provided with hourly fire behaviour predictions for the current time and up to five days ahead for their geolocation. Immediately, we remove the need for users to visit multiple websites, to download the data inputs necessary to produce fire behaviour predictions themselves, to make decisions around what fuel moisture contents and other fuel

model parameter values are appropriate, or to read through detailed reports to get a quick snapshot of expected fire behaviour.

At the top of the home webpage, we provide two interactive visuals to allow users to easily interrogate and interpret current fire behaviour predictions on the go (Fig 2). The first panel is a satellite-imagery map pinpointing the location predictions have been generated for with a banner for latitude, longitude, elevation, slope, and aspect. Users can geolocate themselves, use the search bar to search by place or decimal coordinates, or scroll around the map to manually select a location, which automatically updates fire behaviour predictions to that location. The second panel is a bar chart showing current fire behaviour predictions for all available fuel models. The user can click on the fuel model names in the y-axis of the bar chart to get a description of the fuel and the input parameters and scroll through pictures to help identify which fuel model is most relevant to their location if needed. The default model output is for fire spread rate (m/min), but users can also toggle between heat per unit area (MJm^{-2}), fireline intensity ($\text{MJm}^{-1}\text{s}^{-1}$), fire flame length (m), dead fuel moisture (%), probability of ignition (%), and crown fire transition height (m) by clicking the drop-down box. There is also an information button next to the drop-down that users can click for a definition of the fire behaviour variable and any relevant considerations that have been made in generating the prediction.

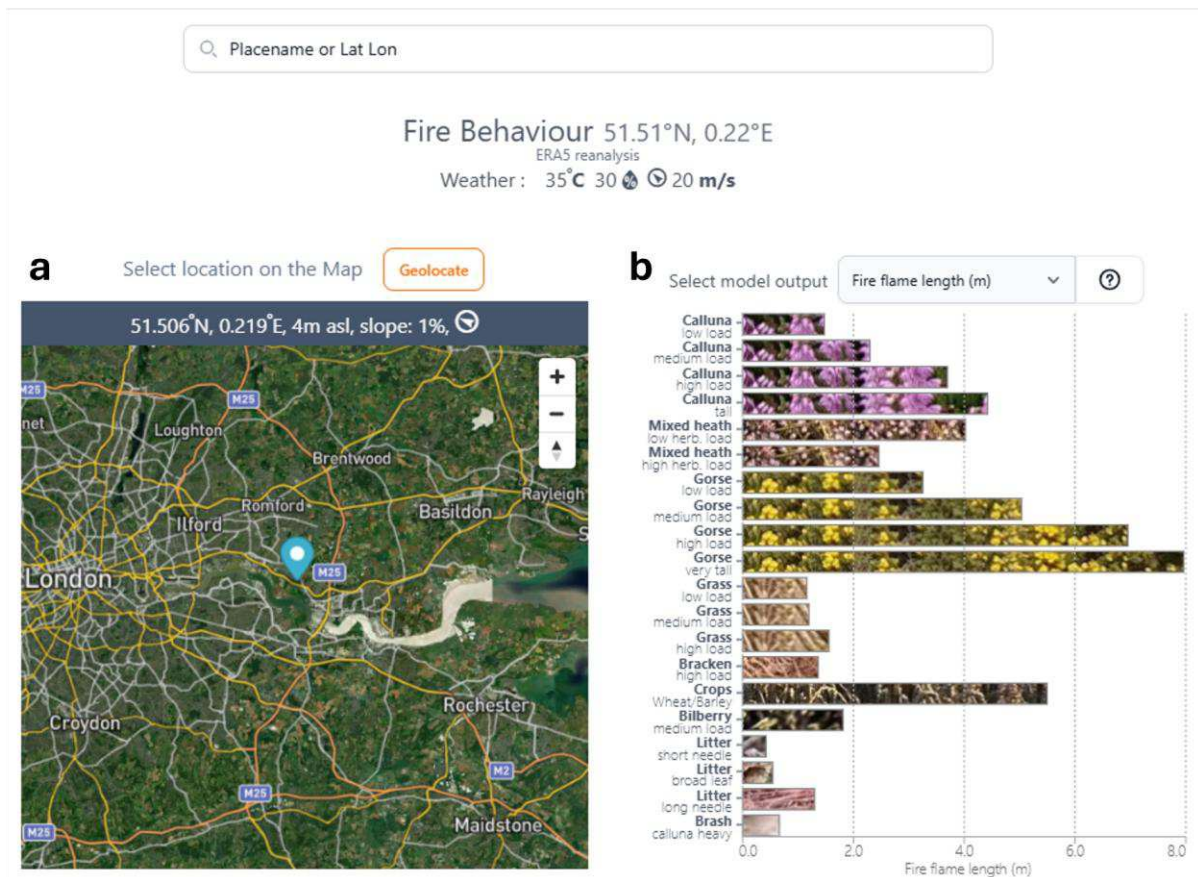


Figure 2. Screenshot of the top panel of the FireInSite home page for the day of the Wennington wildfire of 19 July 2022, which spread across 40 hectares and destroyed 17 houses—the largest structure loss from vegetation fires in recorded UK history (Shukman, 2026). It shows (a) the location of the fire behaviour prediction and (b) the bar chart of predicted flame lengths under the drop-down output menu.

By scrolling down the home page, users are then provided with both hourly weather and fire behaviour predictions for all fuel models for the upcoming five days (Fig 3). Again, users can interact with the y-axis variables for further information. The colour ramps are designed to highlight more extreme fire weather and fire behaviour to quickly draw the user to the most important information.

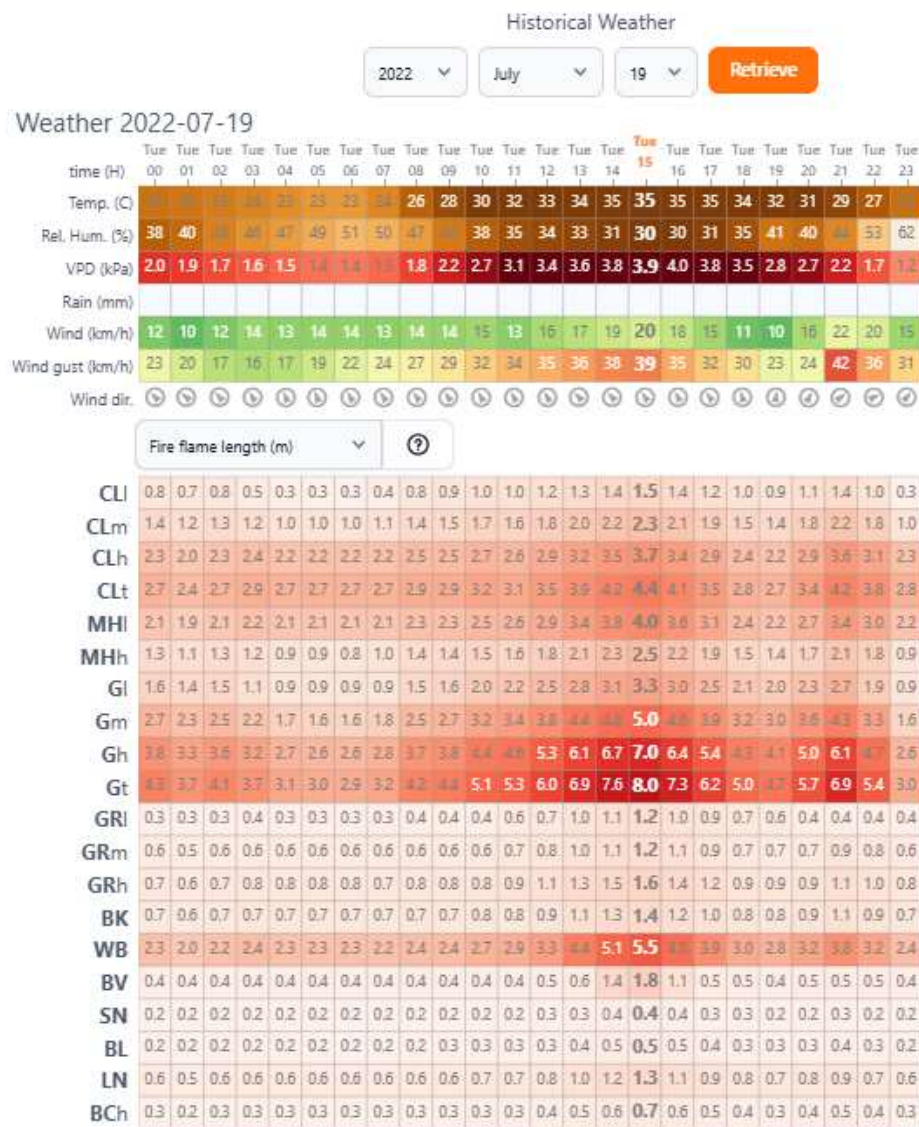


Figure 3. Screenshot of the FireInSite home page for the day of the Wennington fire in the UK (c.f. Fig 2), showing hourly forecasted weather and fire behaviour for all fuel models.

The top banner of the home page provides additional functionality settings and information pages:

- Fuel Models—for descriptions and parameters for the FireInSite fuel models;
- About—for a general introduction to FireInSite;
- Tutorial—for the FireInSite user guide;
- Climate—to view an interactive figure of the daily climatology relative to the long term mean for the selected location (Fig 4). Users can select daily max VPD; min, mean, or max temperature; and min or max humidity as variables;
- User Feedback—opens a new browser for the FireInSite Fire Behaviour Validation ArcGIS Survey123 form for users to document fire behaviour they have observed (Section 6).

Under the settings tab, users can change the dead fuel moisture model used in predictions (FireInSite dead fuel moisture model is the default, but there is also SimpleFFMC (Jolly et al., 2016) and Fosberg (Fosberg et al., 1971)) as well as the weather model used (either UK Met Office, European Centre for Medium Range Weather Forecasts Integrated Forecasting System (ECMWF IFS), or German Weather Service Icosahedral Nonhydrostatic (ICON)). Under the same tab, users can also switch to the historical weather mode, which allows users to explore past fire behaviour predictions by selecting a specific date and location, and they can change the chart type to show the fire characteristics chart rather than the default bar chart.

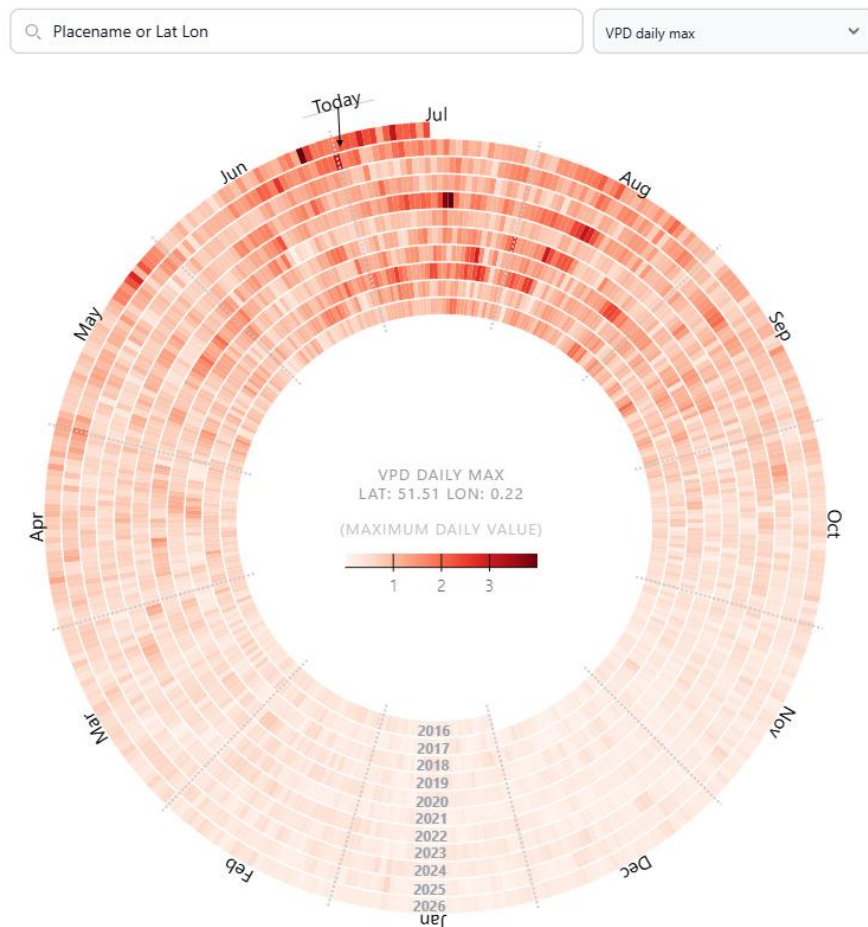


Figure 4. A screenshot of the interactive daily vapour pressure deficit (VPD) climatology accessible in the Climate tab. This screenshot is for a location near to the Wennington fire in the UK (c.f. Fig 2), with the dark red value in July 2022 representing the day of the fire.

The entire FireInSite 1.0 web interface is user facing, meaning there are no data storage requirements from any host organisations. This was an intentional decision to allow organisations to embed FireInSite within their own frameworks easily as well as to protect the longevity of the FireInSite project beyond the lifetime of individual funding.

4. Underlying Data

4.1 Field Data Collection

The data underlying FireInSite 1.0 is drawn from four years of intensive data collection at sites across the British Isles (Fig 5) for key fire prone fuel types, supplemented with previous research published on fuels in these regions.

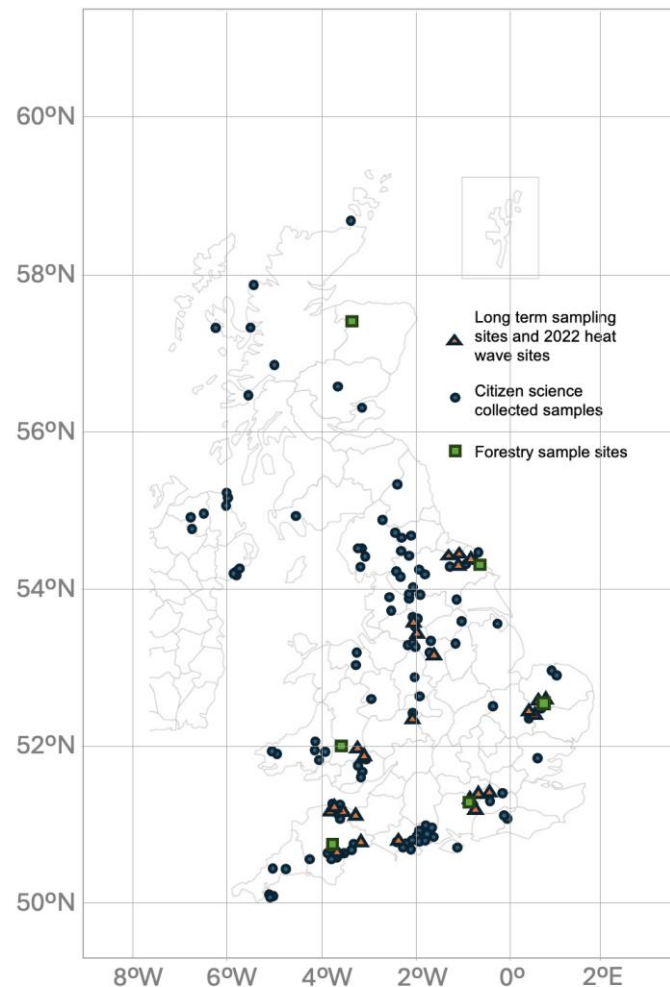


Figure 5. Site locations of vegetation sampled for fuel moisture and flammability testing.

Field campaigns were designed to capture the phenological variation of fuels across the range of UK landscape characteristics. We established a fuel monitoring network of 43 heathland, bog, acid grassland, and coniferous forest locations across the UK. Live and dead vegetation samples from *Calluna vulgaris*, *Ulex europaeus*, *Pteridium aquilinum*, and *Molinia caerulea* were collected from across the UK (Iverson et al., 2024) on a fortnightly basis between April and October and monthly between November and March from 2021 to 2023 following the protocol outlined in

(Little and Quiñones, 2022). These species and additional species *Erica cinerea*, *Erica tetralix*, and *Ulex galii* were also sampled fortnightly over a 12-month period from three dry mixed heathlands in southwest England (Belcher et al., 2025). The data collected from this fuel monitoring network included both fuels sampled in typical seasonal weather conditions (Iverson et al., 2024; Belcher et al., 2025), heat wave conditions (Iverson et al., 2025b), and during the drought of 2025 (Little et al., 2026). Forest litter samples were also collected monthly for a 12-month period from six managed forest plantations of Scots & Corsican pine (*Pinus sylvestris* L. and *Pinus nigra* subsp. *laricio* (Poir.) Maire), Sitka and Norway spruce (*Picea sitchensis* (Bong.) Carrière and *Picea abies* (L.) H.Karst.), and Silver birch (*Betula pendula* Roth) plantations (Crawford et al., 2025).

The long-term monitoring network was supplemented with a more spatially extensive citizen science fuel sampling campaign undertaken in a dry period between the 15th–21st of April 2023. This captured an additional 713 samples from across the UK (Iverson et al., 2025a). We further supplemented the long-term fuel collections with selected sampling of *Vaccinium myrtillus*, *Calluna vulgaris* brash left by the cutting of *Calluna vulgaris* on the surface of moorlands, and wheat and barley during the harvest period of these crops. These field data culminated in an excess of 10,000 live and dead fuel samples representative of the UK's main fire-prone vegetation types for the laboratory analysis of fuel moisture and flammability.

4.2 Fuel Moisture Content (FMC) Measurements

The FMC focus for development of the UK tailored fuel moisture model was based around the most fire-prone fuel types in the UK, heathlands and grasslands, the former of which burn predominantly as live fuels. This required the design of a phenologically-sensitive fuel moisture data collection campaign for live fuels as well as dead fuel moisture interactions. In all cases we collected FMC measurements via destructive sampling in the field because, although labour intensive, this is the only direct way of capturing real FMC variability in detail; data were gathered through the long-term monitoring network, the citizen science campaign, and ad-hoc sampling during heatwave and drought periods as described in Section 4.1. For all samples we calculated gravimetric fuel moisture content (Eq. 1) by weighing the collected samples, drying them for 48 h at 80 °C (Norum and Miller, 1984), and then reweighing the dried samples. The FMC is calculated as:

$$\text{FMC} = ((W - D) / (D - T)) * 100 \quad (1)$$

where W = wet weight (g), D = dry weight (g), and T = the weight of the sample tin (g). A total of 5,845 samples were processed for FMC across the campaigns detailed in Section 4.1.

4.3 Flammability Measurements

As described in Fig 1, to effectively describe the fuel in the model and predict fire behaviour, the energy released during combustion by different vegetation types needs to be included and built into the phenologically-variable heat content model applied within FireInSite's fuel models. An iCone Calorimeter (Fire Testing Technology, East Grinstead, UK) was used to measure the effective heat of combustion (EHoC) of ~1200 samples in duplicate to capture phenological variability over at least a full annual cycle. This was designed to capture variability between key heathland fuel types and UK-wide variability within *Calluna vulgaris* and forest leaf litter.

To capture variability between a range of key fire-prone heathland fuel types, samples from the three dry mixed heathlands described in Section 4.1 were sampled and analysed on the same day as they were collected to avoid effects of changes in fuel moisture (Belcher et al., 2025). Spatial variability in energy content was explored from *Calluna vulgaris* samples collected from the UK-wide fuel moisture sampling network and litter from the forestry plantations described in Section 4.1; both were collected monthly over a full year, stored in sealed tins (*Calluna vulgaris*) and sealed bags (forest leaf litter), and posted for delivery to the University of Exeter for the next day after collection where they were tested within two to three days for the flammability and energy content (Crawford et al., 2025).

Every sample was tested in duplicate: equal volumes of fuel were placed in a mesh basket and placed under a heat flux of 50 kWm^{-2} (equivalent to $\sim 750^\circ\text{C}$) with an electric spark igniter positioned above the surface. The time to ignition (s), peak heat release rate (max fire intensity) (kWm^{-2}), and the effective heat of combustion (MJkg^{-1}) were measured for each sample. All samples were given four minutes of heating to assess whether ignition would occur. If ignition did not occur after four minutes, then the test was stopped. For the samples that ignited, the rate of heat release was analysed until flaming ceased. Details and results are published in Belcher et al. (2025) and Crawford et al. (2025). The phenological variations in EHoC found were then implemented within FireInSite's fuel models (Section 5.1).

4.4. Secondary Data Retrieval

FireInSite retrieves the meteorological data that drive the models on demand from the Open-Meteo weather API (Zippenfenig, 2023). Forecast conditions, and the recent antecedent days that seed the trailing-VPD windows, are retrieved from Open-Meteo's numerical weather prediction forecast endpoint. When a historical date is selected, the corresponding fields are served from Open-Meteo's ERA5 reanalysis archive (Hersbach et al., 2020), the same reanalysis dataset used for FireInSite fuel moisture and grass curing model training, so that the historical and forecast modes remain mutually consistent.

A five-day weather forecast of hourly relative humidity (%), temperature ($^{\circ}\text{C}$), rain (mm), wind speed (kmh^{-1}), wind gusts (kmh^{-1}), and wind direction variables are retrieved for the user's location from one of three weather models: UK Met Office 2 km resolution UK and 10 km resolution for the global model; ECMWF IFS 9 km global model; and German Weather Service (DWD) ICON model with 2 km (central Europe), 7 km (Europe), and 11 km (global) resolution. The weather variables are used to display a five-day forecast, as inputs in the live and dead fuel moisture prediction models, and in the fire behaviour prediction models (Section 5). VPD is obtained directly as an Open-Meteo variable where the source forecast model provides it reliably; otherwise it is computed user-side from 2-m air temperature and relative humidity using the Tetens saturation-vapour-pressure formulation, which reproduces the API values to within about 0.04 kPa.

FireInSite derives slope and aspect for a user-selected location using the Copernicus Global Digital Elevation Model at 90 m resolution (GLO-90; Copernicus Data Space Ecosystem (2021)), which provides global coverage. While higher resolution terrain models do exist, the 90 m resolution model accessible through Open-Meteo Elevation API was used due to FireInSite's run time requirements. Slope and aspect are computed using a central-difference approximation of terrain gradients (Horn, 1981), where partial derivatives in the east-west and north-south directions are estimated from elevation values sampled at four points located 90 m from the selected location in the cardinal directions (due north, south, east, and west). A four-neighbour formulation was adopted instead of the full eight-neighbour variant described by Horn (1981) in order to reduce the number of required elevation queries within the operational web application. Consequently, the resulting terrain parameters are representative of the surrounding landscape

at a moderate spatial scale (approximately 180 m) and do not capture fine-scale or local terrain variability.

5. Model Development

5.1 Fuel Models

Many of the fuel models used in FireInSite were modified from existing fuel models from the international literature to better represent UK fuels using our field and laboratory measured data (Supplementary Materials). We describe the fuel models in use at the time of writing here, but we anticipate new models will continue to be developed based on user needs. All fuel models described herein are detailed in the Supplementary Materials and are continually updated as described at <https://www.fireinsite.org/fuelModels>.

One of the most prevalent landscapes at risk of fire in the UK are upland heaths and moorlands, dominated almost entirely by *Calluna vulgaris*. To build the *Calluna vulgaris* fuel models, we combined the fuel loads measured by Minsavage-Davis et al. (2024) in Scotland and England with our own measured fuel loads and grouped fuel heights by splitting fuel load into percentiles and selecting the corresponding fuel height thresholds that gave minimal fuel load variation within each group (Fig 6A,B). This resulted in low (CLl; 0–20 cm, example shown in Fig 7A), medium (CLm; 20–35 cm), high (CLh; 35–50 cm), and tall (CLt; +50 cm example shown in Fig 7B) fuel load groups. The 1-h dead and live stem fuel loads were calculated as the median values for each group. We used the SA/V ratios of Minsavage-Davis et al. (2024) but increased the dead fuel moisture of extinction to 40% in line with fuel models for humid climate shrubs (c.f. Scott and Burgan (2005)). We also removed the herbaceous fuel load component to better represent *Calluna vulgaris*-dominated fuel patches, as the locations where *Calluna vulgaris* was dominant in our sampling across the UK (Fig 5) indicated that there was very little herbaceous component, and a sensitivity analysis revealed negligible impact. Therefore, the *Calluna vulgaris* fuel models within FireInSite are developed for full *Calluna vulgaris*-dominated landscapes, examples are shown in Fig 7A,B.

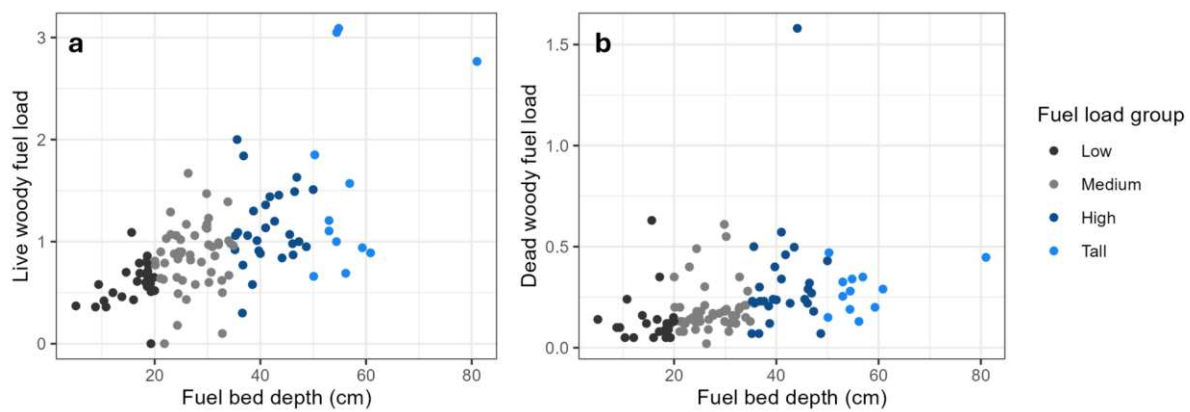


Figure 6. *Calluna vulgaris* fuel bed depths (height) and live woody (A) and dead woody (B) fuel loads used to group low (CLl; 0–20 cm), medium (CLm; 20–35 cm), high (CLh; 35–50 cm), and tall (CLt; +50 cm) fuel load groups.

Many of the UK's fire prone landscapes are in dry heathlands that have a mixed dwarf shrub dominated fuel type, such as those in the Dorset and Surrey Heaths. These dry heathland communities tend to be populated with a mix of dwarf shrubs of the Ericaceae family including *Erica cinerea*, *Erica tetralix*, and *Calluna vulgaris*, as well as the dwarf gorse species *Ulex gallii* (Fabaceae), *Ulex minor* (Fabaceae), and the grass *Molinia caerulea* (Poaceae) as the main fuel types, whilst other parts may be dominated by *Ulex europaeus* (Fabaceae) as the taller woody shrub component or *Pteridium aquilinum* (Bracken fern, Dennstaedtiaceae). These mixed heath communities contain both dead and live fuel in varying proportions, some that have a high amount of herbaceous fuels such as *Molinia caerulea* and *Pteridium aquilinum*, whilst others contain mainly mixed dwarf shrubs (including *Erica cinerea*, *Erica tetralix*, *Ulex gallii*, and *Ulex minor*)—both can carry intense fires. We included two mixed heath fuel models: both have the same parameters as the high fuel class of Minsavage-Davis and Davies (2022), but one has a low herbaceous fuel load to reflect those heaths that are shrub dominated (MHL) (e.g. Fig 7C) and one has a high load of herbaceous fuel (MHh) (e.g. Fig 7D), reflecting those with a considerable *Molinia caerulea* and *Pteridium aquilinum* content. The phenological sensitivity of this was explored in Belcher et al. (2025).

One of the UK's most flammable and most dangerous fuel types in terms of fire behaviour is *Ulex europaeus*, which is particularly common across the UK. We used the Vega et al. (2024) *Ulex europaeus* fuel models from north west Spain, where we defined low load (Gl; mean - SD from $n = 191$), medium load (Gm; mean from $n = 191$), and high load (Gh; mean + SD from $n = 191$) fuel models based on typical variability in *Ulex europaeus* stands across the UK. We adapted the models to use the 1-h SA/V ratio from Simeoni et al. (2011) and live woody SA/V ratio from Anderson's (1982) Chaparral model. We also included a 'tall' version of the high load fuel model

(Gt), which increases fuel depth to 2.5 m based on UKFDRS unpublished data of *Ulex europaeus* fuel heights.

The grass fuel models required fewer adjustments. We used the GR3, GR6, and GR8 models from Scott and Burgan (2005) to represent low load grass (GRl), medium load grass (GRm), and high load grass (GRh), respectively. For all grass fuel models, we removed the 10-h dead fuel load component due to its absence in UK grasslands. We increased the live herbaceous fuel load component of the grass high load fuel model (UKFDRS unpublished data). The *Pteridium aquilinum* fuel model (BK) is the same as presented in Belcher and Hudspith (2016). The crop (wheat/barley WB) fuel model is adapted from Scott and Burgan's (2005) GR6 fuel model, with the fuel loads and fuel depth taken from Cruz et al. (2020).

We additionally added several litter fuel models, based on an analysis of litter samples from managed forestry units from across Britain, which included *Pinus sylvestris* and *Pinus nigra* subsp. *laricio*, *Picea sitchensis*, *Picea abies*, and *Betula pendula* plantations (representative of long-needled, short-needled, and broadleaved trees and described in detail in Crawford et al. (2025)). The short needle litter (SN), broad leaf litter (BL), and long needle litter (LN) were adapted from the Tl1, Tl2, and Tl3 models from Scott and Burgan (2005), respectively. We altered the fuel depth to 0.05 m, which is the top of the 75th percentile of pine litter measurements collected by Crawford et al. (2025).

We also developed the Bilberry/Vaccinium (BV) model (Fig 7E) from field measurements of height and density collected from several different locations in the Peak District, UK by the authors. The SA/V ratios were taken from Scott and Burgan's (2005) SH3 model. We also developed a *Calluna vulgaris* heavy brash fuel model (BCH) (Fig 7F). We adapted Scott and Burgan's (2005) Tl1 fuel model using measurements taken by the authors of the depth and density properties of *Calluna vulgaris* brash from 47 plots across Broomhead Moor in the Peak District, UK.

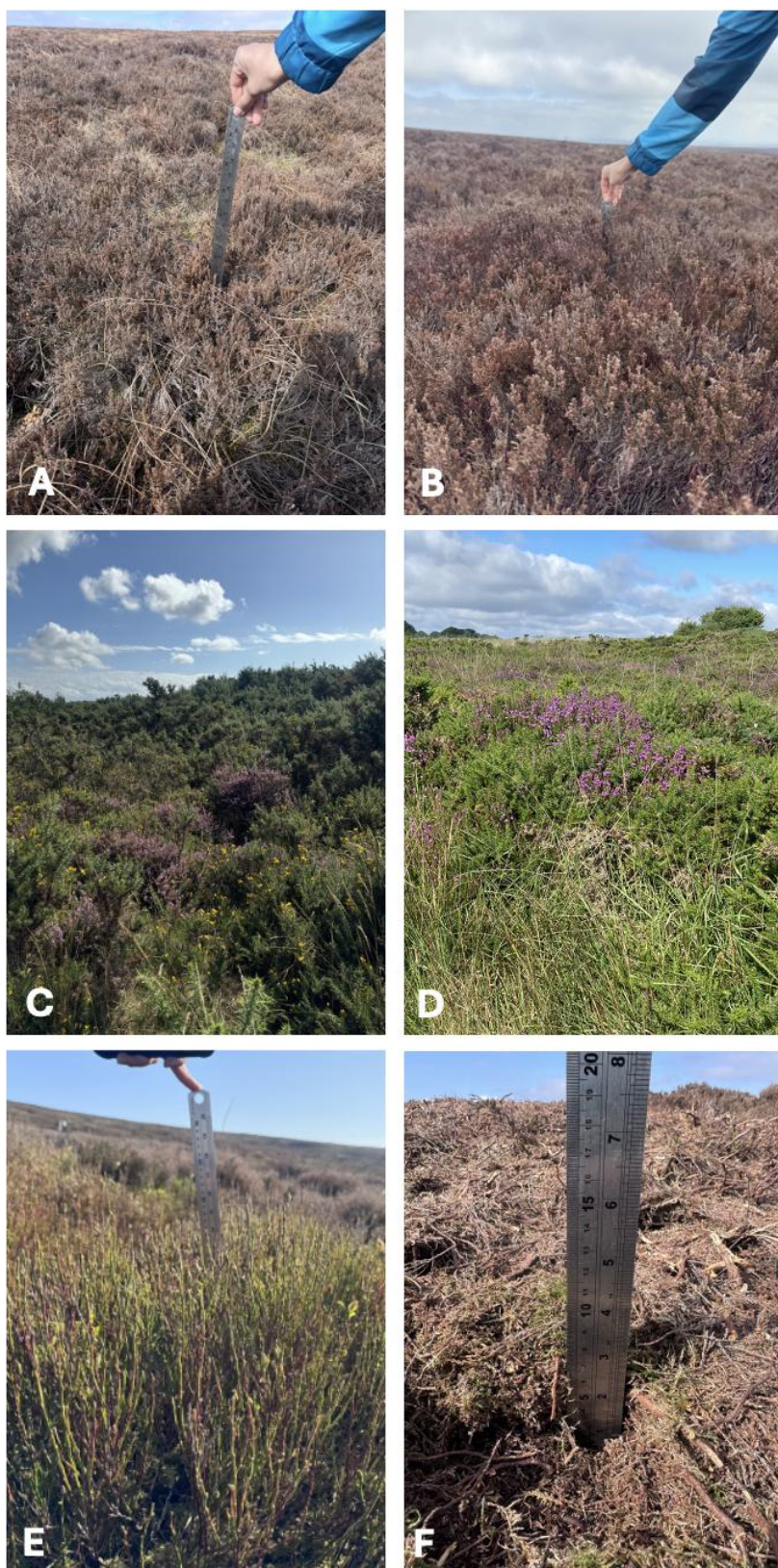


Figure 7. Selected UK fuel examples A) low load *Calluna vulgaris*, B) high load *Calluna vulgaris*, C) mixed heath with a low herbaceous fuel load, D) mixed heath with a high herbaceous fuel load, E) *Vaccinium myrtillus* starting to leaf out, and F) Heavy *Calluna vulgaris* brash.

As part of the fuel model build, FireInSite includes phenologically-variable heat content drawn from measurements of energy release of the key fuel types throughout the year. The heat content of plant material is known to vary between species (Rivera et al., 2012) and also seasonally (Belcher et al., 2025). We took the measured effective heat of combustion for each fuel and converted it to heat content using Equation 2 presented in Belcher et al. (2025):

$$\text{Heat Content} = 0.4383 (\text{EHoC}) + 14.614 \quad (2)$$

Figs 8A and 8B show the measured dead and live fuel heat content variability throughout the year. Most species appear to show similar trends in phases of lower or higher heat content. Dead fuel heat content was found to be lower in May during Green-Up than during other parts of the year (Fig 8A). Whereas live fuel heat content tends to be lower during May–June and falls again between late August through to late October (Fig 8B).

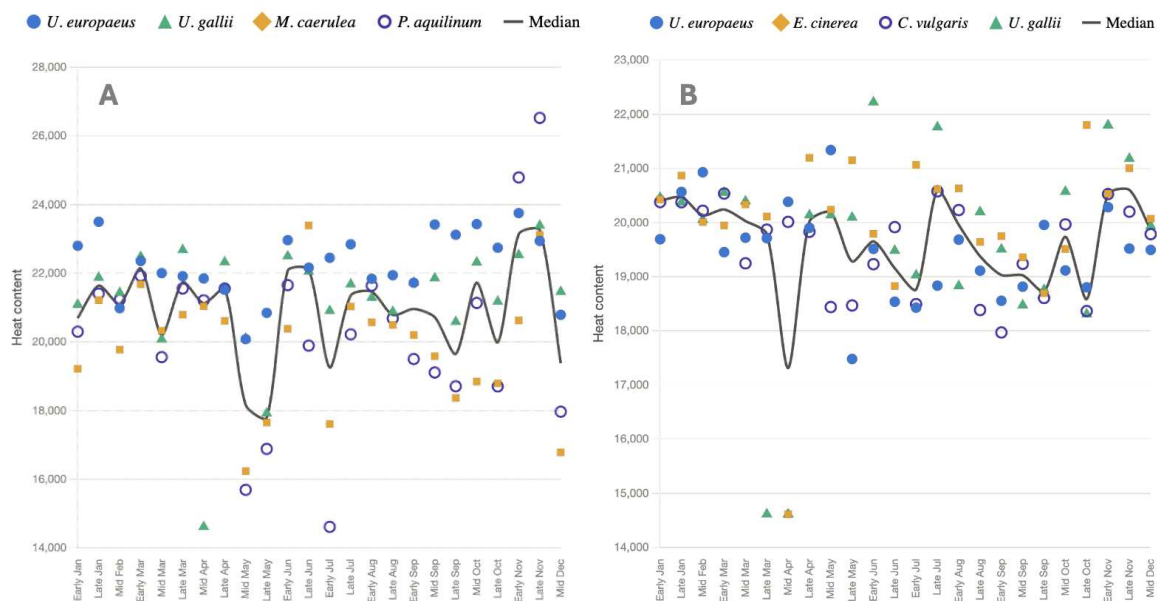


Figure 8. Variability in heat content for dead fuels (A) and live fuels (B).

We reflected these observed phenological trends in FireInSite, such that the time of the year the user places a prediction request for is used to inform each fuel model's heat content automatically. The fuels of interest have different proportions of dead and live fuel, with some fuels burning almost entirely only as dead fuels (e.g. *Molinia caerulea*, *Pteridium aquilinum*, wheat and barley crops, and needle and broadleaf litters), with other fuels such as *Ulex* sp. having a large dead fuel component as well as live fuel, whilst other fuel models including those

dominated by *Calluna vulgaris*, *Erica* sp., and *Vaccinium myrtillis* burn predominantly as live fuels. To reflect this, we used dead fuel heat contents to drive those that burn mainly as dead fuels or mixed dead and live, but live fuel heat content for those that burn mostly as live fuel fuels. The monthly variable values for heat content used within the current FireInSite fuels models are shown in Fig 9 and included in the Supplementary Materials.

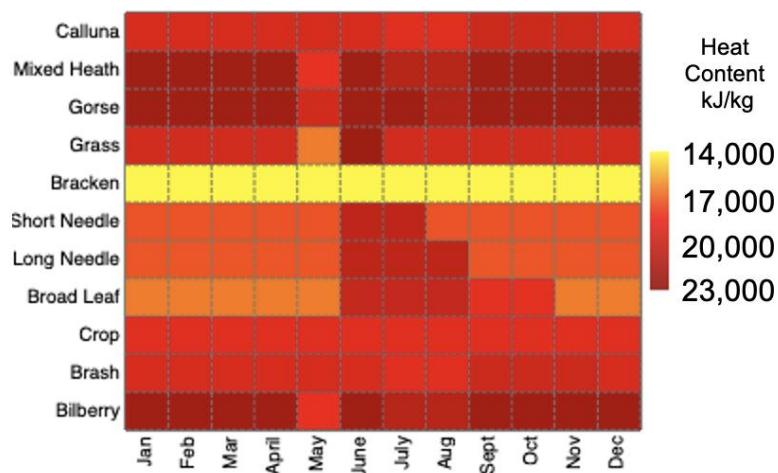


Figure 9. Heat map of heat content used with the current FireInSite fuel models (see Supplementary Materials for detail).

5.2 FireInSite Phenology Index and Fuel Moisture Prediction

Flammability of vegetation in humid regions is strongly affected by changes in plant phenological state (Nikonovas et al., 2024; Belcher et al., 2025) and by large variability in the moisture content of live and dead fuels (Iverson et al., 2024). Several models for dead fuel moisture content (dFMC) have been developed and implemented in operational fire danger rating systems. The existing approaches are typically semi-empirical models with physical constraints (Nelson, 2000; Carlson et al., 2007; Jolly et al., 2016; Perello et al., 2025), which predict dFMC for fuel sticks of defined sizes and time-lag categories. However, none have been calibrated for the heterogeneous mix of fuel particle sizes typical of fire-prone vegetation in humid Atlantic climates. Field measurements in the UK (Iverson et al., 2024) further show marked differences in FMC between vegetation types, along with wide variability even within samples collected at the same site and time. This intra-sample variability is far greater than predicted by existing models focused on specific stick sizes. Live fuel moisture is likewise poorly served by transferring relationships calibrated elsewhere, and grass curing, the senesced, available-to-burn fraction of the herbaceous layer, could not be estimated from the standard BehavePlus live moisture

relationship, because UK live fuels are consistently wetter than that relationship assumes (Section 4).

To address these gaps, we developed machine learning-based FMC prediction models tailored for both live and dead fuels in the most common fire-prone vegetation types in the UK, together with a companion grass-curing model. We used gradient boosting regression (GBR) models to predict live and dead fuel moisture from antecedent weather and terrain inputs (features). The models were trained to predict measured FMC of the UK fuel moisture dataset (Ivison et al., 2024), extended with more recent measurements collected during spring and summer of 2025. A total of approximately 3,600 FMC measurements were used for model development—2,174 for dead fuels (1,781 for dead heather, gorse, bracken, and purple moor grass, and 393 for forest litter) and 1,462 for live fuels (the seven live components in Section 3, spanning 37 sites in 19 ERA5-Land grid cells). Other ground and surface fuels sampled in the same campaign (moss, twigs, and the organic soil layer) were not included in the dead fuel model, as their moisture regimes differ from those of the standing dead vegetation and forest litter. The main meteorological predictor was VPD, which has been shown to perform well for both dead (Rodrigues et al., 2024) and live (Griebel et al., 2023) FMC prediction. Meteorological variables for training were obtained from the ECMWF ERA5-Land reanalysis (Hersbach et al., 2020) at 0.1° spatial resolution and 1-hour time step.

Although empirical in nature, the models allow incorporating physically informed monotonicity constraints. The constraints inform the model whether a specific input should have a positive or negative effect on the output variable, improving model generalisability, and maintaining consistency with underlying fuel moisture dynamics. The models were implemented in Python 3.12 using the histogram gradient boosting regression implementation of the scikit-learn library (Pedregosa et al., 2011). Trained models were exported in the Open Neural Network Exchange (ONNX) format and packaged with FireInSite to enable user-side inference of FMC directly in the user's browser.

A distinguishing feature of the FireInSite models is that predictor selection was governed not only by predictive skill but also by the constraints of operational, user-side deployment. Because predictions are generated on demand in the user's browser from live forecast data, each retrieved variable adds request cost and latency, so inputs were kept to the minimum set that preserved skill. Two further considerations followed from the practicality that models are trained

on ERA5-Land reanalysis but driven in deployment by forecast products: variables that differ most between reanalysis and forecast, notably soil moisture and multi-week precipitation aggregates, introduce a systematic mismatch between model training and inference inputs. These criteria influenced the final set of input variables used in the models.

The performance of the developed models was assessed using a location-aware train/test split. Such an approach provides a more realistic representation of the model's predictive skill at out-of-dataset locations than a standard random split. Each fuel moisture observation site was assigned to the nearest ERA5-Land grid cell. The dataset was then partitioned iteratively by withholding all observations from one location (one ERA5-Land grid cell) for validation while training on the remainder—a leave-one-location-out scheme. As a result, predictions were made for the whole dataset without training on data with the same meteorological inputs as the held-out location.

Dead Fuel Moisture Model (dFMC)

The dead fuel moisture content (dFMC) model was developed to predict sub-daily variability in moisture levels in key fire-prone fuel types: heather, gorse, purple moor grass, bracken, and forest litter (Fig 10). It provides location-specific predictions for a given date and time, using meteorological inputs such as vapour pressure deficit (VPD) and global tilted irradiance (GTI; irradiance adjusted for the slope and azimuth of the site) for the current and previous four hours (i.e., t , $t-1$, ..., $t-4$). While extending the feature set to include additional past hours was considered, hourly VPD and solar irradiance values beyond four hours prior to the prediction time showed negligible importance. In addition to these short-term meteorological inputs, the model uses two seasonal predictors; day length (DayDur) and its day-to-day change (DayDurChange), which capture the phenological and radiative cycle. Following the operational selection criteria of Section 1, DayDur and DayDurChange are computed astronomically from latitude and date and carry the correct seasonal phase in both hemispheres. Finally, a categorical variable identifying the fuel type was used alongside the meteorological and seasonal predictors.

Physical constraints were imposed by applying negative monotonic constraints to VPD and GTI at all time steps, enforcing a decrease in predicted FMC with increasing atmospheric moisture demand and irradiance. The seasonal predictors were left unconstrained. Although precipitation

is arguably a key driver of dead fuel moisture content, it was not included as a predictor in the regression. In addition to the application operational constraints this was also due to the absence of reliable antecedent rainfall observations preceding the FMC field measurements; substantial discrepancies between different weather forecasting and reanalysis models; and limited ability of coarse-resolution gridded data to capture localised convective showers. Instead, precipitation was incorporated into the system after the initial GBR prediction as a physical constraint: if precipitation is forecast for the current time step, the predicted dFMC is increased in proportion to the amount, following the Rainfall Moisture Factor formulation of Jolly et al. (2016).

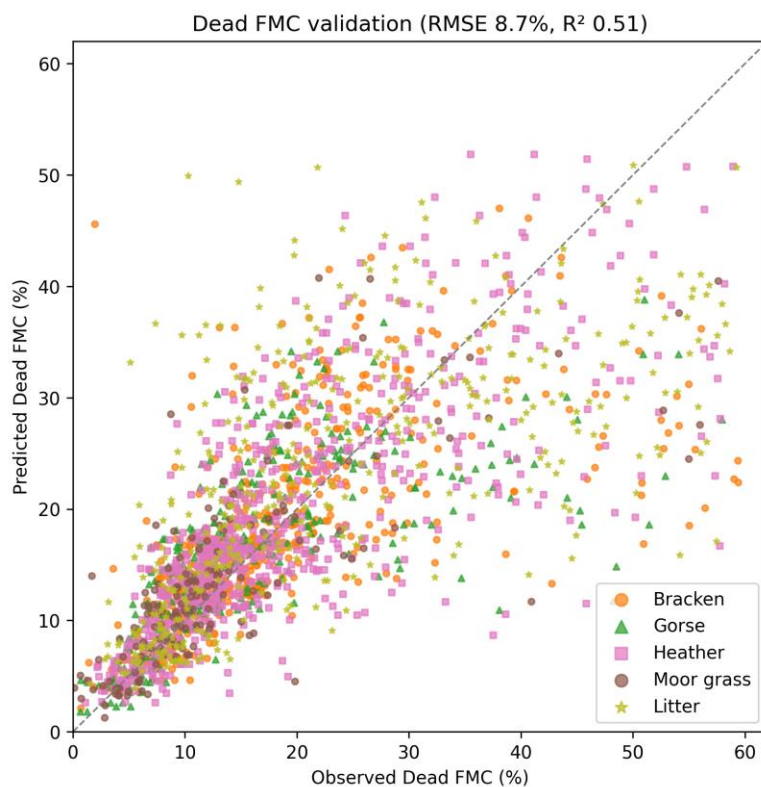


Figure 10. Observed versus predicted dead fuel moisture content under leave-one-site-out cross-validation ($n = 2,174$ measurements across 44 sites; overall RMSE 8.7%, R^2 0.51), coloured by fuel category: bracken, gorse, heather, and purple moor grass (dead standing vegetation), and forest litter. The dashed line is 1:1. Agreement is tightest at the low moisture contents that dominate fine dead fuels; the greater scatter at higher moisture is contributed mainly by forest litter (stars), the most variable category.

Live Fuel Moisture Model (LFMC)

The live fuel moisture content (LFMC) model provides daily predictions for the live components of the main fire-prone vegetation types in the UK: bracken (leaves and stem), gorse (canopy and stem), heather (canopy and stem), and purple moor grass (Fig 11). As in the dFMC model, a categorical variable identifying the vegetation component was included alongside the

meteorological predictors, allowing a single model to serve all seven live fuel categories. Live fuel moisture is strongly autocorrelated in time and, being buffered by plant physiology, changes only gradually from day to day. Two complementary steps were implemented to encode this behaviour. First, the VPD predictor used in the model is not the single-day maximum but its seven-day trailing mean (VPD_{max-7mean}), representing the antecedent atmospheric moisture demand the fuel has integrated rather than the weather of an individual day. Second, the model output is treated as an equilibrium moisture content toward which the fuel relaxes with a characteristic response time (Equation 3; Fig 12):

$$L_t = L_{t-1} + (1 - e^{(-\Delta t/\tau)}) (Leq,t - L_{t-1}) \quad (3)$$

where L_t is the smoothed live fuel moisture predicted for day t ; L_{t-1} the previous day's smoothed value; Leq,t the model's raw (unsmoothed) prediction for day t , treated as the equilibrium the fuel is relaxing toward; Δt the time step (one day); and τ the chosen response time of 7 days. This is the same first-order formulation used in response-time dead-fuel moisture models (Nelson, 2000), in which the moisture approaches its equilibrium value exponentially with a fixed time lag τ —the time to close a fraction $(1 - 1/e)$, about 63%, of the gap to equilibrium; the factor $(1 - e^{(-\Delta t/\tau)})$ is the fractional approach achieved over one time step. This output relaxation removed approximately 80% of the residual day-to-day variance in the predicted series with no loss of validation skill (July RMSE was marginally improved, Fig 13), avoiding physically implausible abrupt changes in live fuel moisture. The two steps are complementary rather than redundant: the first represents the fuel's memory of antecedent conditions, the second the fuel's response time. To initialise the trailing mean at the start of the forecast, the preceding days' daily maximum VPD are retrieved and prepended to the forecast window.

Same as with the dFMC model, a negative monotonic constraint was applied to the VPD predictor, enforcing a decrease in predicted lFMC with increasing atmospheric moisture demand; the seasonal and vegetation-type predictors were left unconstrained. Each FireInSite fuel model is mapped to the most representative live component for the live-category moisture it receives (e.g. Calluna-dominated and dwarf-shrub fuels to heather canopy; grass fuels to purple moor grass); dead-only fuels (litters, brash) are excluded as they carry no live load.

The model predictions were compared against a per-fuel monthly climatology computed from the training folds alone, so that no information from the withheld location entered the baseline.

Across 1,462 live fuel observations from 19 ERA5-Land grid cells, the IFMC model achieved an RMSE of 32.8% ($R^2 = 0.70$) under the leave-one-location-out scheme, compared with 35.3% for climatology. The margin was strongly seasonal: in July, when UK fire risk is greatest, the model advantage more than doubled (RMSE 32.0%, $R^2 = 0.76$, against 39.1%, $R^2 = 0.64$, for climatology). The model out-performed climatology at 14 of the 17 sites with sufficient observations for a per-site comparison. Predictive skill was not uniform across vegetation types: the largest improvements over climatology were obtained for gorse canopy and purple moor grass, particularly in July (RMSE reduced by 21.6% and 23.8%); heather stem was predicted approximately as well by climatology as by the model, reflecting its limited variability; and for bracken leaves the model performed slightly worse than climatology (RMSE 51.6% against 46.9%), so predictions for that fuel should be treated with corresponding caution.

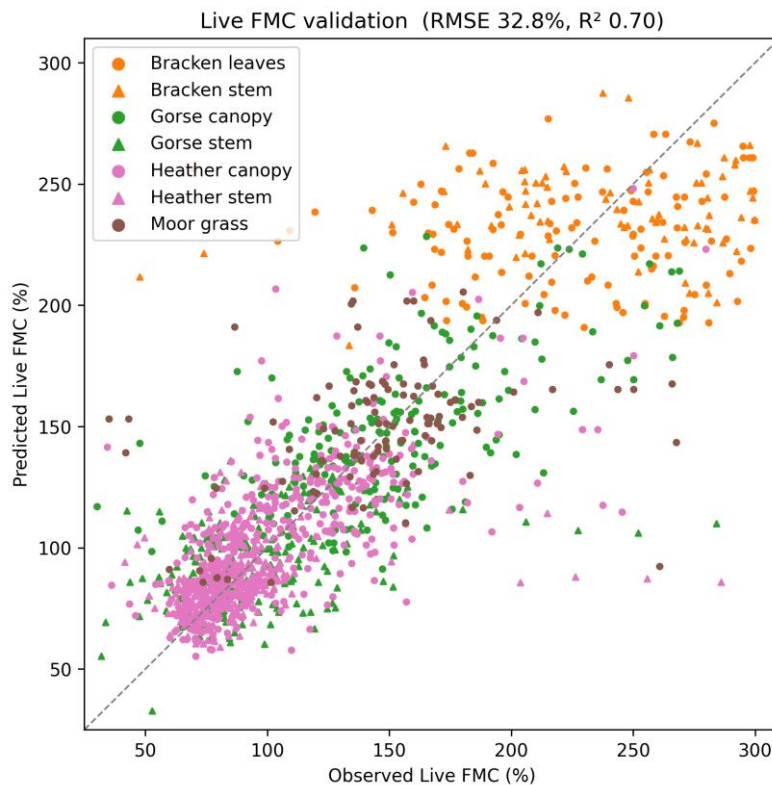


Figure 11. Observed versus predicted live fuel moisture content under leave-one-location-out cross-validation ($n = 1,462$ measurements across 19 ERA5-Land grid cells; overall RMSE 32.8%, R^2 0.70), coloured by vegetation component (circles: canopy or leaves; triangles: stem). The dashed line is 1:1. Bracken (orange) is the least well constrained component.

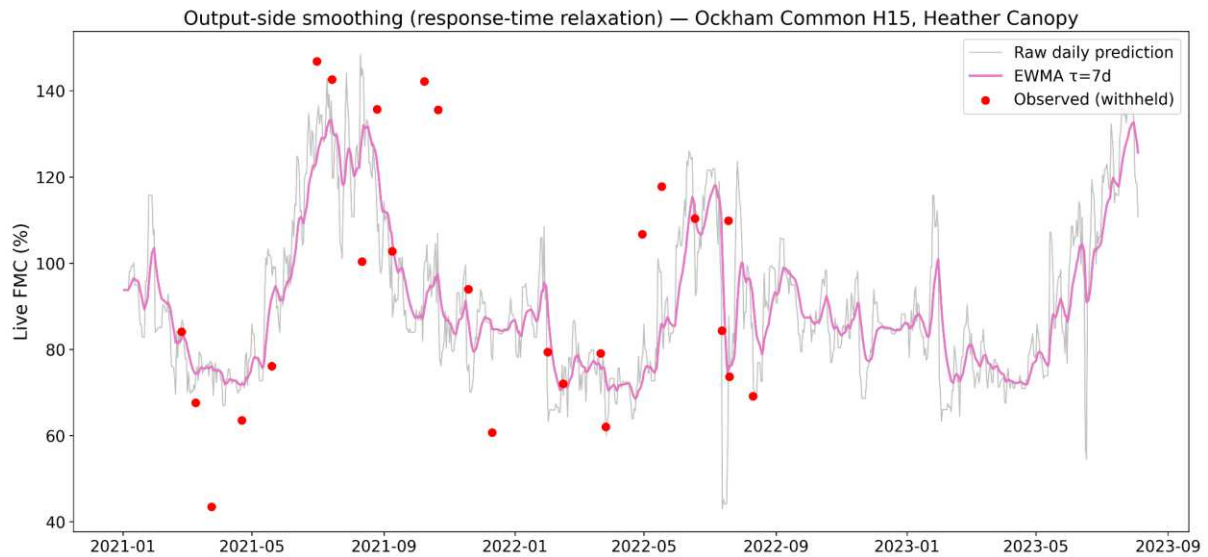


Figure 12. The continuous daily live FMC prediction for one withheld site (heather canopy, Ockham Common), before and after the response-time relaxation applied in deployment. Grey: the raw daily prediction, which inherits the day-to-day volatility of the weather inputs. Pink: the same series after a first-order (EWMA) relaxation with time constant $\tau = 7$ days, matching the response time of the live fuel. Red points are the withheld live FMC observations at the site.

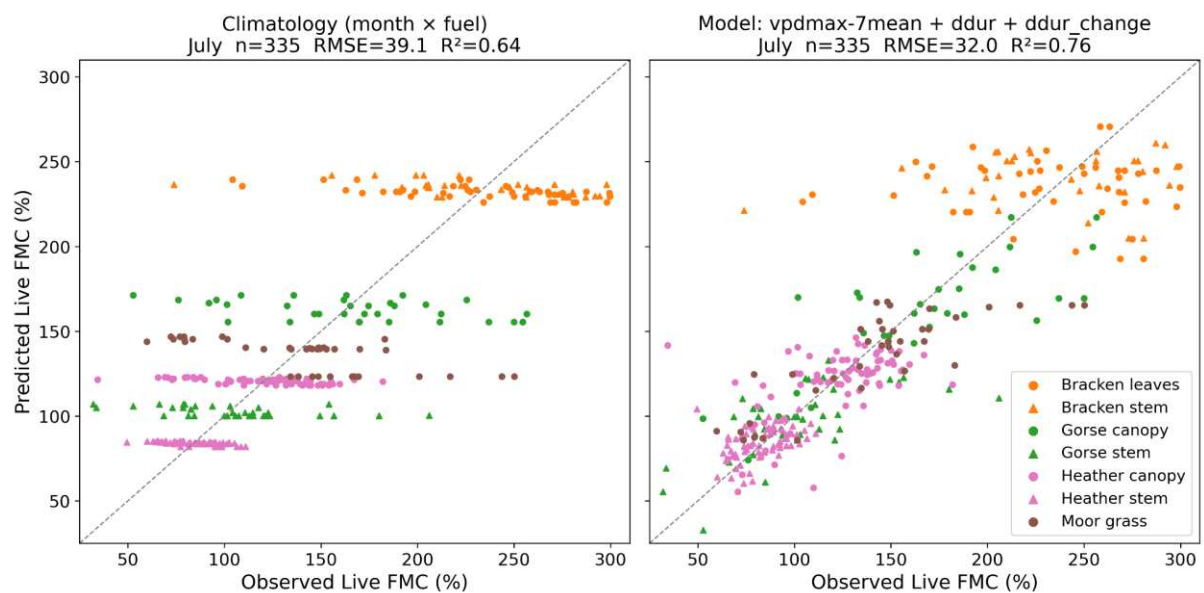


Figure 13. July-only live fuel moisture validation (leave-one-location-out), the period of greatest UK fire risk. Left: per-fuel monthly climatology (RMSE 39.1%, R^2 0.64). Right: the FireInSite lFMC model (RMSE 32.0%, R^2 0.76). Climatology collapses each fuel onto a near-constant July value and cannot represent the observed range, whereas the model tracks it; the advantage is greatest for gorse canopy and purple moor grass.

5.3 Grass Curing Model

Herbaceous fuel curing—the fraction of the herbaceous fuel load that has senesced and is available to burn—is a key control on fire behaviour in the dynamic fuel models, where it governs

the transfer of live herbaceous load into the dead 1-hour fuel class. BehavePlus offers the option of estimating the cured fraction directly from live herbaceous moisture content. We did not use this option in FireInSite. UK live fuels are consistently wetter than the moisture range that relationship assumes, so the estimated cured fractions were unrealistically low and the models generated little or no fire behaviour under conditions in which fires are known to occur (Belcher et al., 2025). We instead predict the cured fraction with a dedicated model, trained (like the dead- and live-FMC models) as a gradient-boosted regression, but on satellite observations of vegetation greenness rather than field moisture samples. The curing model is deployed for the fuel models with herbaceous load (GRI, GRm, GRh, and MHh). Because the herbaceous fraction of the mixed heath fuel (MHh) is small, curing has only a marginal effect on its predicted behaviour.

No direct field measurement of cured fraction exists at the scale required for training, so the model target was derived from satellite greenness. We used the two-band Enhanced Vegetation Index (EVI2) time series (Nikonovas et al., 2024) as a direct inverse proxy for herbaceous curing. For each grid cell, the EVI2 record was converted to a cured fraction by a robust per-cell rescaling; the 5th and 95th percentiles mapped to fully green (0% cured) and fully cured (100%), respectively, which removes between-site differences in absolute greenness so that a single weather-to-curing relationship can transfer across locations. Training data comprised 47 grass-dominated locations drawn from the CEH Land Cover Map (improved and acid grassland classes), each with a twelve-year EVI2 record (2012–2024) sampled approximately every eight days, about 18,500 cell-days in total. Mixed heath/shrub cells were excluded from training because their whole-pixel greenness is confounded by evergreen dwarf shrubs.

The FireInSite curing model uses three inputs: day length, its day-to-day change, and the seven-day trailing mean of daily-maximum VPD—the same VPD series that drives the live fuel moisture model. A systematic feature search found that longer-term predictors—soil moisture and longer VPD windows—did not improve leave-one-cell-out skill significantly. The final model therefore needs only day length (free) and a VPD series already retrieved for the live fuel model and carries no additional data requirement.

Model skill was assessed by leave-one-cell-out cross-validation, holding out each grid cell in turn so that every prediction is made at an unseen location. Over the 47 grass-dominated locations, the model attains RMSE of 18.5% and R^2 0.64 against the EVI2-derived cured fraction. The skill is

concentrated in the seasonal progression; however, sub-seasonal, drought-driven departures from the climatic norm, such as the 2022 event, are also represented by the weather in the model (Fig 14).

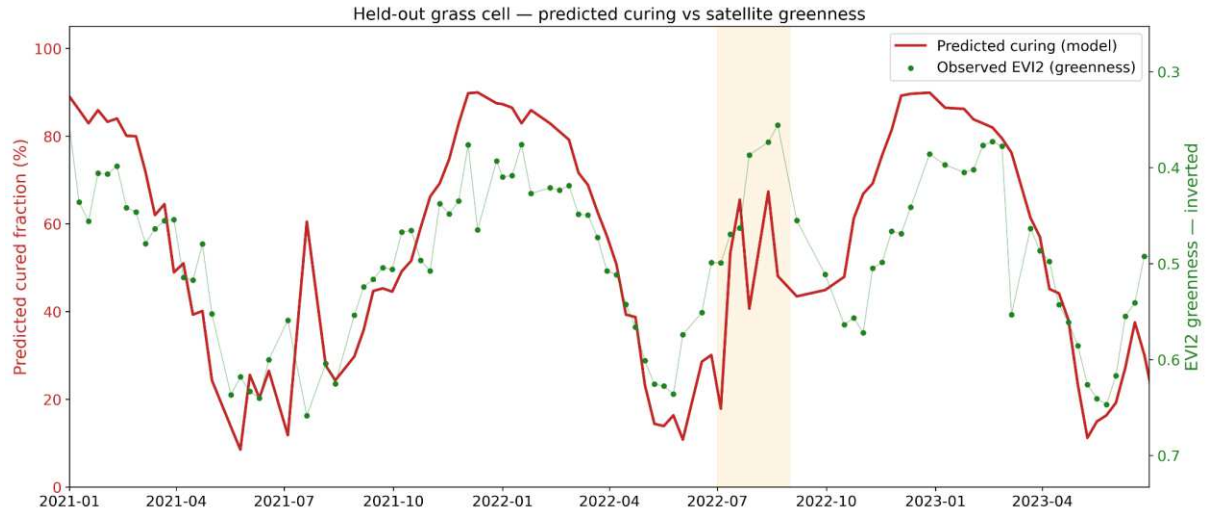


Figure 14. Validation of the grass-curing model, a gradient-boosted regressor trained to predict cured fraction from day length, its day-to-day change, and 7-day-mean VPD. The target is satellite greenness (EVI2) converted per grid cell to a cured fraction. The figure shows the daily predicted curing (red, left axis) against raw satellite EVI2 greenness (green, right axis inverted so that browning aligns with higher curing) for one withheld grass-dominated location (at 51.04°N, 1.32°W—improved grassland in Hampshire, South-East England, not used in fitting) including the 2022 drought (shaded).

5.4 Canopy Fire Transition Height Calculation

The standard Behave Plus modelling system provides estimates for the critical surface fireline intensity required to initiate a crown fire at a given canopy base height. As a more intuitive indicator for crowning fire occurrence, FireInSite outputs a custom quantity—crown fire transition height. This parameter indicates canopy base height below which crown fire is likely given surface fire intensity. It is derived from the Equation 11 in (Scott and Reinhardt, 2001):

$$I_{\text{initiation}} = ((CBH * (460 + 25.9 * cFMC)) / 100)^{(2/3)} \quad (4)$$

which calculates the critical surface fire intensity required to initiate canopy combustion at a given canopy base height (CBH) and foliar canopy moisture content (cFMC). In contrast, FireInSite solves the above equation for CBH:

$$CBH = (100 * (I_{\text{intensity}})^{(2/3))} / (460 + 25.9 * cFMC) \quad (5)$$

In this rearrangement, the critical surface fire intensity required to ignite the canopy at CBH (Equation 11, Scott and Reinhardt (2001)) is replaced with the surface fire intensity predicted by the model. Canopy base height is a physical attribute of the forest stand that can be visually estimated and hence, we believe, allows for a more straightforward assessment of if the canopy is susceptible to crowning under current weather and surface fire conditions.

6. FireInSite Fire Behaviour Validation

Most fire behaviour prediction systems that are underlain by the Albini (1976); Byram (1959); and Rothermel (1972) equations do not present any formal validation of predictions. However, we felt it was important to understand how well predictions generated from FireInSite mapped onto observations of fire behaviour in the UK. To achieve this, we compiled a database of flame length observations from previous wildfires in the UK up until the end of the 2025 fire season, using photographs and videos retrieved from media reports, Fire and Rescue Service personnel, including the UK's specialist Wildfire Tactical Advisors, and land managers (Supplementary Materials). From each source, we recorded the fuel type (or range of fuel types), date, approximate latitude, longitude, and time of day. We determined the flame length by visually estimating the distance from the average flame tip to the midpoint of the flaming zone at the fire base (Wade, 2013). We also retrieved wildfire records, including reported flame lengths, from the Dorset Fire Intervention Dataset provided by the Dorset Heaths Partnership (Dorset Council, 2025). After compiling observations of flame lengths, we retrospectively obtained flame length predictions from FireInSite for the corresponding coordinates, date and time of the observations, and relevant fuel type(s). This gave us either a single predicted flame length or a range if there were multiple possible fuel types or times of day from the information given.

FireInSite's predicted flame lengths are well correlated with reported flame length observations (Fig 15), with a Pearson correlation of 0.74 (p-value = 0.0001). While there are large uncertainties associated with using reported flame lengths (such as estimating average flame lengths and fuel loads visually from imperfect media and potential uncertainty in the media reported time of observation and exact location), this relationship provides confidence in the ability of FireInSite to predict likely fire behaviour for operational decision-making, such as selecting suitable and safe suppression strategies. Validation of FireInSite predictions is ongoing, and users can report observations of fire behaviour through a reporting tool on FireInSite that links to an ArcGIS Survey123. This growing database of fire behaviour observations is being used to identify areas

where adjustments could improve fire behaviour predictability, such as highlighting fuels that require further constraining.

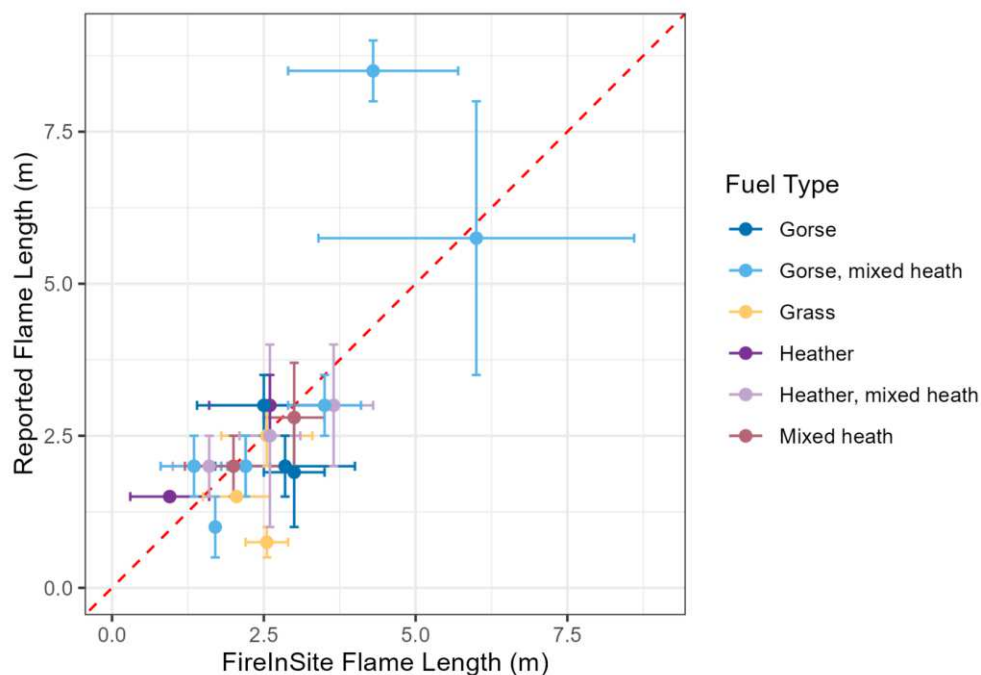


Figure 15. The relationship between the maximum, minimum and mean reported flame length observations (22 observations from media reports, Wildfire Tactical Advisors, and Dorset Explorer) and FireInSite predicted flame lengths by fuel type, with a line of perfect correlation fitted (red dashed).

7. FireInSite Initial Community Testing and Response

The needs of the user community were paramount in the conception and design of FireInSite. Throughout its early build phase, we engaged UK Fire and Rescue Services, particularly the UK's Wildfire Tactical Advisors (TacAds). In addition, we formed an advisory panel including participants from a range of Fire and Rescue Services (stretching England, Wales, and Scotland), UK Wildfire TacAds, Forest Research, The UK Met Office, Natural England, The Forestry Commission, and the UK Home Office and Ministry of Housing, Communities and Local Government. The FireInSite development team attended three UK TacAd events, presenting early inception design plans, a beta test version, and the current version. We gathered feedback, made adjustments, and requested responses as to its utility during wildfires. In addition, we asked Fire

and Rescue Services to feedback fire data as part of continued validation of the model results (see <https://www.fireinsite.org/#>).

Early feedback on an initial interface from the advisory panel resulted in the addition of the ability to select your location on a base map, followed by five-day forecasting. The feedback from the first beta testing of the current interface resulted in the additions of the VPD calculations being added to the prediction tables and the Climate tab that brings up the VPD history (<https://www.fireinsite.org/climate>). The current iteration of FireInSite was launched in 2025 and coincided with the UK's longest drought period and the largest ever total area burned recorded. At the end of the fire season, we requested feedback via one of the Wildfire TacAd events that included 20 expert (TacAds) practitioner participants. They were asked to provide an overall rating of the software/web app; 63% of TacAd users gave a score of 4* out of a maximum of 5 whilst 37% rated it as 5*. All participants scored FireInSite as good (16%), very good (32%), or excellent (53%) in terms of meeting their overall user needs.

We asked the TacAds what purposes they had used FireInSite for and they reported the following: a) *Fire Behaviour prediction during an active event*, b) *Future fire risk assessment/land management planning*, and c) *In Fire and Rescue Service training and education*. Of those that used FireInSite during an active event, 60% found that it made a significant difference whilst 40% reported it as useful. For those that utilised FireInSite in planning for future fire risk, 40% responded to say that it made a significant difference whilst 60% reported it as useful. Of those that utilised FireInSite in providing training and education within the Fire and Rescue Services, 59% said that it had made a significant difference in their ability to provide training and education, whilst 41% found it useful. Finally, 80% of respondents said that they would 'very likely' recommend FireInSite to a co-worker or other relevant user whilst the remaining 20% said that they were likely. Respondents also reported what the benefit of using FireInSite had been to them so far, and these included:

- '...It allowed me to inform senior management of the risk on certain days and prepare for an increase in fire activity'
- "Informing Royal Parks of fire rates and travel distances"
- "Prior to deploying to scene, it has been a useful quick reference guide prior to getting ground truth"

- ‘Identifying vegetation type in a designated area and the changes in severity linked to weather conditions at the time. It's a great starter for planning wildfire tactics until more accurate ground truth can be gathered’
- ‘Ability to plan and allocate care resources at active fire events’
- ‘Access to detailed data for specific locations, which you can then look at different vegetation types present. This is such a powerful tool, especially as you can access it on a mobile phone’

The current version of FireInSite has been well received and utilised by TacAds and Fire and Rescue Services in the UK to support wildfire decision-making both ahead of and during wildfires, building a strong core user base for its continued development. FireInSite is also beneficial to land managers looking to assess their wildfire risk, plan prescribed burning, and assess the impact of fuel management on likely wildfire behaviour. As such, we have also shared FireInSite at a range of engagement events designed to begin to connect with those managing land, with reports that conservation trusts, moorland groups, and farming and agriculture sectors in the UK are using FireInSite (e.g., Gilruth (2025); North East Cotswold Farmer Cluster (2025); Game and Wildlife Conservation Trust (2026)). Furthermore, FireInSite is being used as part of the suite of Lantra-accredited fire training programmes for land managers as well as the Fire Service College’s Wildfire Skills and Wildfire Support Officer training (Elliott, 2026a, 2026b).

We continue to develop FireInSite in close collaboration with the UK wildfire TacAds and other stakeholders. Future versions of FireInSite will look to develop advanced user functionality and new features requested by our key user archetypes, including logins to save user preferences. In this way, development will continue to be user centric. A recurring user request has been the integration of a spatial forecasting map for monitoring levels of regional fire danger, which would enable spatial resource planning for Fire and Rescue Services, communication of public warnings regarding the use of open flames (BBQs), restrictions in national parks, or planning of prescribed fire operations. This capability would complement FireInSite’s detailed point-based predictions and will form a core component of FireInSite 2.0, which is currently in development.

8. Conclusions and Further Development

Here we have presented FireInSite 1.0, a user-oriented web-based fire behaviour prediction system to support fire management decision-making in humid temperate regions like the UK and Ireland. We have highlighted the novel aspects of FireInSite 1.0, such as (i) UK tailored fuel models, including species-specific and phenologically-driven heat content, (ii) UK specific live and dead fuel moisture models linked to phenology, and (iii) a user-friendly system with integrated geolocated weather forecasts, topography, and in-built fuel models, making fire behaviour predictions more accessible to decision makers. FireInSite enables the assessment of fire risk and the effects of fuel load reduction and planning for fire prevention and suppression.

FireInSite 1.0 has been developed for the humid temperate fuels of the UK and Ireland, meaning the platform is transferable to other humid temperate regions with similar fuels such as Northwestern Europe. However, fire behaviour predictions can also be obtained globally, thanks to the global weather forecast models integrated into FireInSite. With small modifications, such as the inclusion of customised fuel models, FireInSite could be adapted for countries with fuels beyond those already included within FireInSite or in the Southern Hemisphere where the phenological cycles of vegetation are the opposite to the UK. As such, FireInSite has wide reaching potential for (a) humid temperate regions with similar fuel types to the UK, (b) other emerging fire-prone regions that lack decision-support tools, (c) those who want to understand the science behind wildfire behaviour predictions, and (d), more generally, those wanting to develop more accessible prediction platforms for end-users. Ongoing validation and user feedback have demonstrated the success of FireInSite 1.0 and its opportunities for future development and expansion to comparable humid temperate regions and beyond.

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