Scotland's Rural College

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Factors affecting severity of wildfires in Scottish heathlands and blanket bogs

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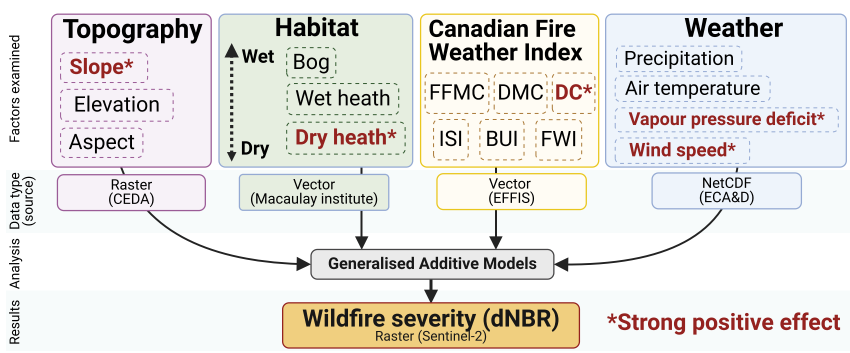
HIGHLIGHTS

- Wildfires in dry heath are more severe than in blanket bog and wet heath.
- Fire severity correlates positively with slope, elevation and south-facing aspect.
- Weather, especially vapour pressure deficit and wind speed, impacts severity.
- The Drought Code is a key predictor in the Canadian Fire Weather Index System.

GRAPHICAL ABSTRACT



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ABSTRACT

Temperate heathlands and blanket bogs are globally rare and face growing wildfire threats. Ecosystem impacts differ between low and high severity fires, where severity reflects immediate fuel consumption. This study assessed factors influencing fire severity in Scottish heathlands and blanket bogs, including the efficacy of the Canadian Fire Weather Index System (CFWIS). Using remote sensing, we measured the differenced Normalised Burn Ratio at 92 wildfire sites from 2015 to 2021. We used Generalised Additive Mixed Models to investigate the impact of topography, habitat wetness, CFWIS components and 30-day weather on severity. Dry heath exhibited higher severity than wet heath and blanket bog, and slope, elevation and south facing aspect were positively correlated to severity. Weather effects were less clear due to data scale differences, yet still indicated weather's significant role in severity. Rainfall had an increasingly negative effect from approximately 15 days before the fire, whilst temperature had an increasingly positive effect. Vapour Pressure Deficit (VPD) was the weather variable with highest explanatory value, and predicted severity better than any CFWIS component. The best-explained fire severity model ($R^2 = 0.25$) incorporated topography, habitat wetness wind and VPD on the day of the fire. The Drought Code (DC), predicting organic matter flammability at $\geq$10 cm soil depth, was the CFWIS component with the highest predictive effect across habitats. Our findings suggest that wildfires in wet heath and

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blanket bogs are typically characterised by low severity, but that warmer, drier weather may increase the risk of severe, smouldering fires which threaten peatland carbon stores.

1. Introduction

Temperate heathlands and blanket bogs are globally rare habitats which support unique species and significant belowground carbon stores. These habitats are widespread in the Scottish uplands (and hence we refer to them as upland habitats) but are under increasing risk of wildfires due to climate change (Flannigan et al., 2013; Liu et al., 2010). Recent years have seen an increase in wildfire occurrence in Scotland and the trend is predicted to continue (Albertson et al., 2010; Arnell and Freeman, 2021; Krawchuk et al., 2009). Between 2015 and 2020, wildfires affected over 68,000 ha of Scotland (EFFIS, 2022b) with half of fires occurring in dry and wet heathlands and the other half in blanket bogs (Taylor et al., 2021). Warmer temperatures and decreased precipitation in Scotland are expected to result in longer fire seasons, increased fuel flammability and lower water tables (Westerling et al., 2006; Wotton and Flannigan, 1993), which may lead to increased wildfire frequency and severity.

'Fire severity' can be measured as the above- and belowground organic matter consumption during the fire and is often more relevant for ecological studies than 'fire intensity' which refers to the heat output of the fire (Keeley, 2009). Subsequent effects occurring after the fire passage, known as 'ecosystem responses', encompass processes like vegetation recolonisation and soil erosion (Keeley, 2009). In fire-prone ecosystems such as boreal forest and Californian pine forest and chaparral, fire severity may affect the composition of recolonising vegetation (Keeley et al., 2008; Schimmel and Granström, 1996) and soil microbiota (Adkins et al., 2020). Research on fire severity effects in Scottish uplands is limited but has identified links between severity and composition of initial post-fire vegetation (Davies et al., 2023; Grau-Andrés et al., 2019) and soil respiration (Davies et al., 2014). Upland wildfires of extremely high severity, which penetrate deep into the peat, can adversely impact the ecosystem and leave burnt areas uncolonised by vascular plants for years due to abiotic soil changes or colonisation of certain mosses or lichens (Clement and Touffet, 1990; Maltby et al., 1990). Enhanced understanding of factors influencing wildfire severity in Scottish uplands can assist in conservation, land management, and fire response planning.

Spatial variations in fire severity result from factors such as topography, fuel type, and fuel load. Steep slopes decrease the distance angle between flames and the substrate (Costa et al., 2011; Lecina-Diaz et al., 2014), and south-facing slopes receive more solar radiation, both of which may result in drier fuels and higher severity (Costa et al., 2011). Upland habitat type may affect fire severity on a fine to moderate scale, with earlier research indicating that dry heathlands may dry out easier and burn more severely than blanket bogs under similar weather conditions (Davies et al., 2016, 2023; Grau-Andrés et al., 2018). This is likely due to differences in vegetation composition, species-specific variations in biomass 8production (Milne et al., 2002) and moisture thresholds at which ignition can be sustained (Davies and Legg, 2011; Santana and Marrs, 2014, 2016).

W/eather considerably influences fire severity on a broader scale. Drier and warmer climate, measured as, for example, mean vapour pressure deficit (VPD) during the fire season, results in higher severity and area of wildfires (Jain et al., 2022; Mueller et al., 2020). Similarly, it is notable that particularly severe wildfires often occur during extended periods of extreme drought and/or high temperatures (Maltby et al., 1990; McMorrow, 2011). However, predicting fire severity based on weather forecasts is challenging, especially regarding the specific duration of drought needed to elevate the risk of severe fires in Scottish uplands.

The Canadian Fire Weather Index System (CFWIS) forecasts daily wildfire risk using six components, including fuel moisture codes and fire behaviour indices, based on time-lagged precipitation, temperature, humidity and wind (Van Wagner, 1974; Table 1). The CFWIS was created for Canadian jack pine (*Pinus banksiana*) woodland but has been adapted globally, including to the Meteorological Office Fire Severity Index in En

gland and Wales (Kitchen et al., 2006). However, the system largely fails to predict fire risk in Scotland's treeless uplands (Davies et al., 2006; De Jong et al., 2016; Taylor et al., 2021). Individual CFWIS components have proven more useful than the final fire risk index; for example, the components tied to surface fuel moisture and wind speed (Fine Fuel Moisture Code, FFMC, and Initial Spread Index, ISI) may predict heathland fire occurrence and area but not severity (Davies and Legg, 2016; Taylor et al., 2021), and components linked to deeper soil moisture (Drought Code, DC, and Duff Moisture Code, DMC) may relate to fire severity and smouldering risk in Scottish uplands (Davies et al., 2013, 2016). Further

research is needed for a tailored fire risk index in Scotland.

This study aimed to compare the relative importance of potential determinants of the severity of wildfires in Scottish upland habitats. We utilised remotely sensed dNBR as a proxy for severity and examined the influence of topographical variables, habitat type, wind speed, 30-day weather (precipitation, air temperature and VPD) and components of the CFWIS. By comprehensively analysing these factors, we aimed to enhance our understanding of wildfire dynamics in these ecosystems, thereby informing more effective management and mitigation strategies.

2. Methods

2.1. Site selection and data acquisition

Sites were selected from a dataset of 316 wildfires which occurred in Scotland between 2015 and 2021, downloaded from the European Forest Fire Information System (EFFIS) website in the form of shapefiles (EFFIS, 2022a) (Fig. 1). A map showing all the sites can be found in the Supplementary material (Fig. S1). EFFIS mapped wildfires >30 ha until 2017; smaller sites have been mapped since 2018. Our study focuses on

Table 1
The moisture codes and fire behaviour indices of the Canadian Fire Weather Index system. Based on Van Wagner (1974). The three first components are fuel moisture codes and measure the dryness in different layers of the forest floor. The fuel moisture codes are then used to create the fire behaviour indices, which in turn are merged to a final index of fire risk.

	Component	Description
Fuel moisture codes	Fine Fuel Moisture Code (FFMC)	The dryness of the smallest forest fuels (surface litter, leaves, needles, small twigs). Wind is included in the calculation.
	Duff Moisture Code (DMC)	The dryness of the medium-sized surface fuels and loosely compacted, decomposing organic matter (approximately 2 to 10 cm depth).
	Drought Code (DC)	The dryness of the deep compacted layers of organic matter ($\geq$ 10 cm depth).
Fire behaviour indices	Initial Spread Index (ISI)	A relative measure of how quickly a fire can be expected to spread, derived from the FFMC and wind speed
	Build Up Index (BUI)	A relative measure of the amount of fuel available for combustion, derived from the DC and DMC
Final index	Fire Weather Index (FWI)	A relative measure of potential fire intensity, derived from the BUI and ISI

sites >30 ha, yielding a total of 166 included sites. We overlaid a 1:24,000 scale land cover map of Scotland (Macaulay Land Use Research Institute, 1993) with wildfire shapefiles, selecting only those wildfire sites encompassing >10 ha of land cover areas classified as dry heath, wet heath, undifferentiated heath or blanket bog. This filtering process resulted in 161 sites proceeding to the next step.

We employed the difference Normalised Burn Ratio (dNBR) to derive a remotely sensed measure of fire severity. The choice of dNBR was based on its well-established efficacy in assessing fire severity, with studies indicating minimal differences among various metrics for assessing severity (e.g., Parks et al., 2014; Fassnacht et al., 2021; Storey et al., 2021). To analyse the dNBR of the wildfire sites, Sentinel-2 images were processed in Google Earth Engine (Gorelick et al., 2017) based on a script provided by United Nations Knowledge Portal (United Nations, 2017). dNBR is defined as the difference between the Normalised Burn Ratio (NBR) of the pre-fire image and post-fire image (Lutes et al., 2006). NBR is calculated using the near infra-red (NIR) and shortwave infra-red (SWIR) spectral bands, with the following equation: NBR = (NIR − SWIR) / (NIR + SWIR). NBR indicates the degree of burning, since healthy, unburnt vegetation has a high NIR response and a low SWIR response, whilst the opposite is true for recently scorched vegetation (Lutes et al., 2006).

Pre- and post-fire images were selected using Earth Observation Browser (Sentinel Hub, 2022). For each site, the pre-fire image was selected from within four weeks before the fire event, or in case of lack of cloud-free images, from the year before (± four weeks of the fire date).

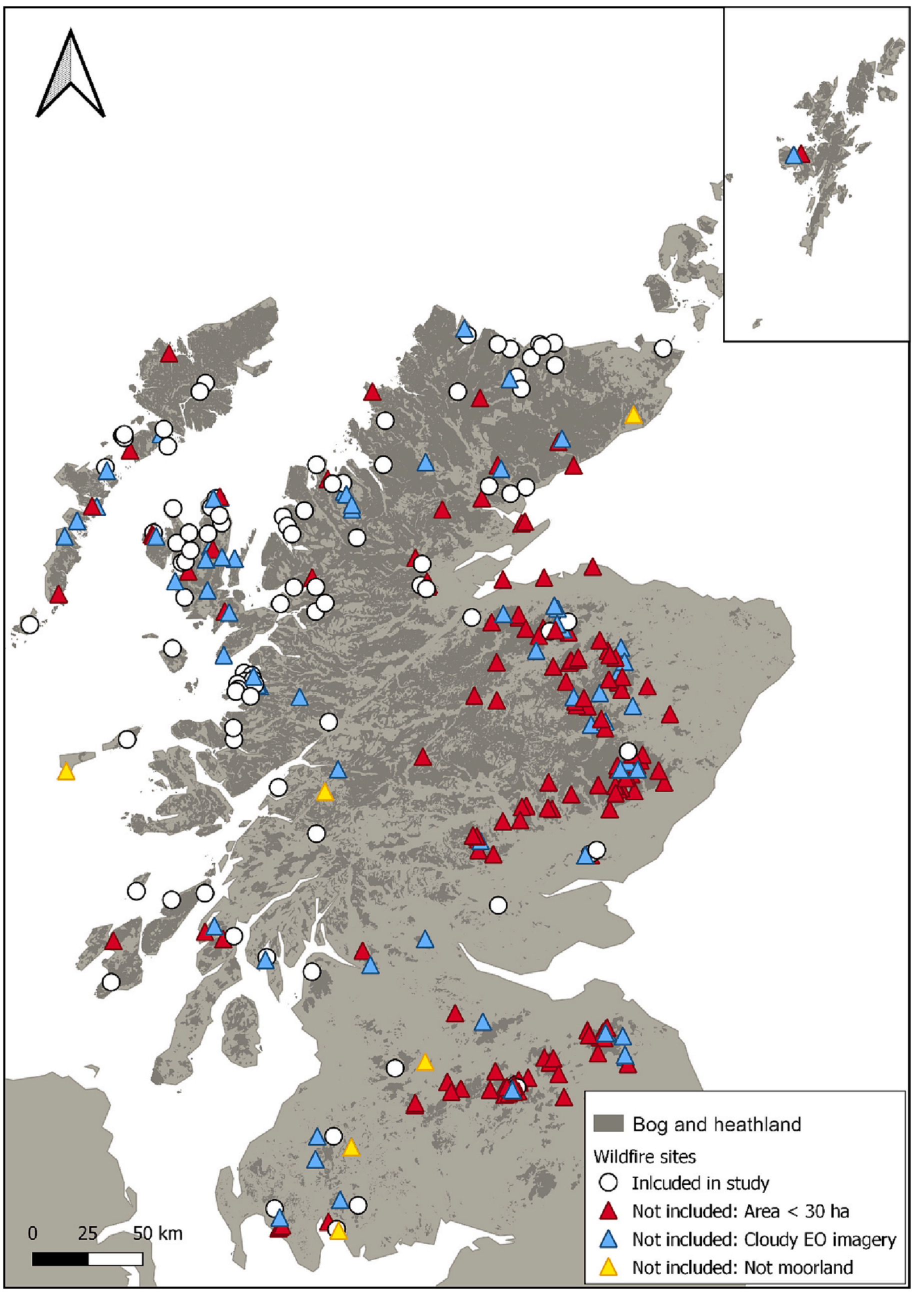

Fig. 1. Map showing locations of wildfires which occurred in Scotland, UK, between 2015 and 2021, as recorded by the European Forest Fire Information System (EFFIS). Shaded areas depict heathland and blanket bog (Macaulay Land Use Research Institute, 1993). White points represent wildfire sites which were included in the study, whilst triangles indicate sites which were not included for various reasons, indicated by symbol colour. Red triangle: Area < 30 ha or site is clearly a prescribed fire consisting of multiple, small strips of burnt moorland, recorded as one continuous site by EFFIS. Blue triangle: No useful earth observation imagery available for a period of six weeks after the fire due to high cloud cover. Yellow triangle: Site area > 30 ha but negligible proportion in moorland.

The post-fire image was selected from one to six weeks after the fire. The resulting dNBR images were downloaded as 30 m resolution rasters. We acknowledge that the resulting dNBR may be affected by the time after fire that the images were from, but preliminary analyses indicated that dNBR remained relatively stable within this time range.

Scotland has a high cloud cover, and sites which lacked cloud-free satellite imagery from the selected time periods before or after the fire were omitted. We also omitted fire sites which were found to be multiple, very small patches of prescribed fire, inaccurately recorded as a single, larger burnt area by EFFIS. Sites which EFFIS registered as separate fire events, but which burnt on the same day and were < 100 m from one another were merged and counted as one site. The resulting total number of sites included in the study was 92 (Fig. 2).

A 5 m resolution digital terrain model (GetMapping, 2014) was used to obtain elevation, slope and aspect data. The resolution of all topographical rasters was reduced to 30 m to equal the resolution of the dNBR rasters. Using QGIS (QGIS Development Team, 2022), each dNBR raster pixel was intersected with elevation, slope, aspect and land cover layers. Slope, aspect and latitude were used to calculate a heat load index for each point, using Function 3 in McCune and Keon (2002). Heat load is an estimate of local temperature based on sun exposure and is, at high latitudes such as in Scotland, highest on steep south-western slopes and lowest on steep north-eastern slopes. We used heat load instead of aspect in our calculations as heat load has been shown to affect evapotranspiration and vegetation growth (He et al., 2017), which can impact fuel moisture content and fuel load. We confirmed that there was no significant collinearity between heat load index and slope.

United States Geological Survey (USGS) suggests that dNBR values below 100 indicate unburnt areas and that unburnt vegetation often has a dNBR of approximately −100 to 100 (Lutes et al., 2006). However, the threshold indicating burning is known to vary depending on vegetation type and local conditions. It has not been previously established for heather dominated vegetation, but a case study of a heathland and bog wildfire in Isle of Rum, Scotland, identified a threshold of dNBR around

Fig. 2. Map of Scotland showing locations of wildfire sites included in the study, with fire severity measured as Differenced Normalised Burn Ratio (dNBR) illustrated with a colour ramp. In the original dataset, dNBR values <50 were initially included. However, as values <50 were consistently prevalent outside of burnt areas, this threshold was utilised to identify burnt areas exclusively. Consequently, values below 50 were excluded from the dataset to ensure a focus on burnt areas in the analysis.

0 (NatureScot, 2019). Examination of our data showed that unburnt areas outside of the perimeters of burns typically had dNBR values between 0 and 50, whilst inside burnt perimeters dNBR was higher, and values <50 were very rare. As our main aim was to statistically assess factors affecting variations in severity, we considered it important to only include definitely burnt pixels and therefore we excluded all pixels <50 dNBR. It is noteworthy that this means that the fire areas referred to in this paper do not include potential unburnt islands within the burnt perimeter. No datapoints had unrealistically high dNBR (> 1300 according Lutes et al., 2006).

Next, all data points located outside of blanket bog or heathland were excluded from the dataset, resulting in a final dataset size of 651,773 points, where each dNBR pixel equals one point. To avoid using the ambiguous habitat type undifferentiated heath, data points labelled in this way were relabelled as wet heath, as recommended by one of the authors of the Land Cover Scotland 1988 dataset (Nolan, A., personal communication). Preliminary analyses confirmed that wet heath and undifferentiated heath were comparable in terms of fire severity. Consequently, the habitats included in the study were dry heath, wet heath and blanket bog.

Daily total rainfall, daily mean temperature, daily mean relative humidity (all at 2 m above ground level) and mean wind speed at 10 m height were acquired from the E-OBS ensemble dataset (v25.0e) in 0.1-degree resolution (European Climate Assessment and Dataset, 2022). For each site, rainfall, temperature and humidity data were extracted for the day of fire and the 30 preceding days, whilst wind data was extracted only from the day of fire. Initially, 60-day rainfall and temperature data were used, but preliminary analyses demonstrated low explanatory values with the 60-day dataset, compared to the 30-day. Vapour Pressure Deficit (VPD) in kPa was calculated using relative humidity and mean temperature (Bonan, 2008). VPD is the difference between the saturation vapour pressure and actual vapour pressure and provides a useful metric for the evaporative potential of the atmosphere, and been shown to correlate positively with fire severity and fire area in a variety of habitats (Grünig et al., 2021; Sedano and Randerson, 2014). Daily CFWIS components (FFMC, DMC, DC, ISI, BUI and FWI) at 8 km resolution were acquired from EFFIS for the initial day of fire for each site (EFFIS, 2022a).

2.2. Statistical analysis

All statistical analyses were carried out using R v. 4.1.2 (R Development Core Team, http://cran.at.r-project.org/). We formulated a series of models (Table 2) to assess the impact of topographical variables and weather variables on fire severity measured as dNBR. For these analyses we utilised General Additive Mixed Models (GAMMs), using the function *gamm* from the R package *mgcv*, v. 1.8-42 (Wood, 2017). Rather than fitting the models to the whole, highly pseudo-replicated dataset which would be computationally challenging, we fitted each model to 50 different subsets of 50 random points per site ($N = 4600$ per subset). The estimates from the models were then represented graphically by overlaying the predictions from all subsets, which allowed for visual assessment of the uncertainty about the estimates. Assumptions of homogeneity of variance and normality of residuals were checked using diagnostic plots (provided in Fig. S2 in the Supplementary material). In all models, site was included as a random effect, and all other variables were included as smooth terms.

Although model results were mainly interpreted graphically, we used the mean marginal R^2 (fixed terms only) and conditional R^2 (fixed and random effects) between subsets to compare the predictive power of each model with different sets of variables. We used function r.*squaredGLMM* in package *MuMIn* (Barton, 2023) to assess the R^2 values of each model.

The first model (Model 1, Table 2) included only habitat, and the second model (Model 2) additionally included topographical predictors: slope, elevation and heat load. We created a continuous variable for habitat wetness by assigning 0 to data points in dry heath, 0.5 in wet heath and 1 in blanket bog, representing a gradient from dry to wet habitat. To account for spatial autocorrelation, we assumed a spatial correlation using an exponential covariance function, blocked by site. To account for the possibility of larger scale spatial non-independence between sites, we also included flexible bivariate splines of latitude and longitude. Model 2 was the basis for all our subsequent models, and was formulated as follows:

Table 2
List of General Additive Models (GAMs) predicting fire severity measured as difference Normalised Burn Ratio (dNBR), and the smooth terms included in each model. Each row represents a different model. All models included a random site effect, a smooth spatial term representing distance between sites and an exponential autocorrelation term of distance between observations within a site. Habitat wetness is a continuous variable where 0 = dry heath, 0.5 = wet heath and 1 = blanket bog. Heat load is a measurement of solar radiation exposure. Fine Fuel Moisture Code (FFMC), Duff Moisture Code (DMC), Drought Code (DC), Initial Spread Index (ISI), Build Up Index (BUI) and Fire Weather Index (FWI) are components of the Canadian Fire Weather Index System.

Model name	Terms included in model
1	Habitat wetness
2	Habitat wetness + slope + elevation + heat load
3	Model 2 + Rainfall day 0–30 + temperature day 0–30 + wind
4	Model 2 + Rainfall day 0–30 + temperature day 0–30
5	Model 2 + Wind
6	Model 2 + VPD day 0–30 + wind
7	Model 2 + VPD on day of fire onset + wind
8a	Model 2 + FFMC
8b	Model 2 + DMC + wind
8c	Model 2 + DC + wind
8d	Model 2 + ISI
8e	Model 2 + BUI + wind
8f	Model 2 + FWI

$$S_i \sim \text{Normal}\left(\mu_i, \sigma_r^2 \Sigma_r\right)$$

$$\mu_i = \alpha + f_1^3(\text{wetness}_i) + f_2^{10}(\text{slope}_i) + f_3^{10}(\text{elevation}_i) + f_4^{10}(\text{heatload}_i) + f_5^{20}(\text{Lat}_i, \text{Lon}_i) + \gamma_j$$

$$\gamma_j \sim \text{Normal}\left(0, \sigma_s^2\right)$$

Index *i* is an observation-level index, *j* is site index. S_i is the response variable and γ_j a site-level random intercept, both of which are assumed to follow a normal distribution with variances σ_r^2 (within-site) and σ_s^2 (between-site), respectively. Σ_r is a block-correlation matrix with correlation e^{-kd} between two locations, separated by distance *d*, within a block (site). α is the intercept. All smooth terms ($f_.^*$) were represented by thin plate splines (Wood, 2017) where * represents the model complexity of the function.

We then built upon this model by adding weather variables, specifically, the wind conditions on the day of fire onset, as well as the cumulative rainfall and temperature in the 0–30 days leading up to the occurrence of the fire (Model 3, Table 2). Our analysis involved assessing the R^2 values for models that included various combinations of these weather predictors (Models 4 and 5). We used the complete daily rainfall and temperature record for 30 days prior to the respective fire onset as predictors, resulting in daily regression coefficients for rainfall and mean temperature respectively, with lagged effects ranging from 0 to 30 days. Including many explanatory variables that are serially related, such as rain and temperature data from multiple consecutive days, may result in severe multicollinearity and poorly identifiable and unstable coefficient estimates. To deal with this issue we adopted a method similar in scope to that described in Sims et al. (2007), which is a distributed lag model, implemented using a “function on scalar” construct in *mgcv* (Wood, 2017). This method deals with the issues of multicollinearity by constraining the daily coefficients for both rainfall and temperature to vary smoothly over the time lag sequence, preventing the variance inflation of coefficient estimates induced by collinearity. Model 3 was formulated as follows:

$$S_i \sim \text{Normal}\left(\mu_i, \sigma_r^2 \Sigma_r\right)$$

$$\mu_i = \alpha + f_1^3(\text{wetness}_i) + f_2^{10}(\text{slope}_i) + f_3^{10}(\text{elevation}_i) + f_4^{10}(\text{heatload}_i) + f_5^{10}(\text{wind}_i) + \sum_l \text{Rain}_{i,l} f_6^{10}(l) + \sum_l \text{Temp}_{i,l} f_7^{10}(l) + f_8^{20}(\text{Lat}_i, \text{Lon}_i) + \gamma_j$$

$$\gamma_j \sim \text{Normal}\left(0, \sigma_s^2\right)$$

where l is time lag (from 0 to 30 days).

The next models estimated the effect of VPD. We created one model (Model 6, Table 2) with 30-day daily VPD as a time-lagged variable as for daily rainfall and temperature above. An alternative model (Model 7) included no time-lagged variables, but only VPD on day of fire onset as a smooth effect.

We then estimated the effect of CFWIS components on severity, by creating a separate model for each component (Models 8a-8f, Table 2). For models with DMC, DC and BUI we included wind in the model, whilst models with FFMC and ISI did not include it, since wind is already accounted for in the calculation of these components. To test whether the CFWIS components have different effects depending on habitat, we also ran the above CFWIS models separately on subsets of each habitat ($N = 700$ per subset for dry heath, 3150 for blanket bog, 3900 for wet heath).

In models with rainfall, temperature and wind, the impact of weather varied notably based on whether the spatial smooth effect (accounting for distance between sites) was included. Consequently, we report results for Model 4 with and without inclusion of the spatial smooth. For the other models, outcomes are presented only with the spatial smooth effect, as no significant differences were observed based on its inclusion.

It is noteworthy that all GAM partial effect plots are centred on the mean, meaning that the increase or decrease shown in the y-axis is reflected in the average predicted value of severity (i.e., the effect is relative to the mean). The exception is lagged effects (in this case 0–30 day rainfall, temperature or VPD) where a negative value on the y-axis indicates a negative effect on severity, a positive value indicates a positive effect and zero indicates no effect (Sims et al., 2007).

Before performing the analyses, we checked the weather and CFWIS data for outliers. We found that one of our sites had noticeably higher windspeed at fire onset than remaining sites (11 m s^{-1} compared to the mean 4 and the otherwise maximum 6). We decided to include this site in the analyses, but consequently, it is important to note that the estimates for wind speed over 6 m s^{-1} are uncertain. One of the sites had extremely high values of DMC, DC and BUI compared to remaining sites. This site skewed the results and was excluded from all analyses where CFWIS components were included.

3. Results

Our study was based on 92 sites and a total of 42,272 ha of burnt upland area (Fig. 2). A full list of sites and their details is provided in the Supplementary material (Table S1). The raw dNBR values in the dataset included in analyses ranged from 50 to 1214, with a mean value of 296. Wet heath was the most prevalent habitat type in the dataset (462,827 data points, 55 % of total), but it also had the lowest mean dNBR in the raw data: 260 (Fig. 3, Table 3). Blanket bog was also a common habitat (355,695 data points, 42 % of total) and had a mean dNBR of 325 (Fig. 3, Table 3). Very few datapoints were in dry heath (26,913 points, 3 % of total) but this habitat had a high mean dNBR of 522 (Fig. 3, Table 3).

The effects of topographical variables and habitat wetness were very consistent between models regardless of what weather variables we included (Fig. 4). Below 30 degrees, slope had a strong, increasingly

Table 3
Wildfire area (of the fires included in the dataset) in hectares and mean, 50th, 75th and 95th percentile values of wildfire severity measured as difference Normalised Burn Ratio (dNBR) in wet heath, blanket bog, dry heath and all habitats.

Habitat	Burnt area	dNBR			
		Mean	50th percentile	75th percentile	95th percentile
Wet heath	23,141 ha	260	234	345	567
Blanket bog	17,785 ha	325	329	448	612
Dry heath	1345 ha	522	571	723	825
All	42,272 ha	296	271	408	623

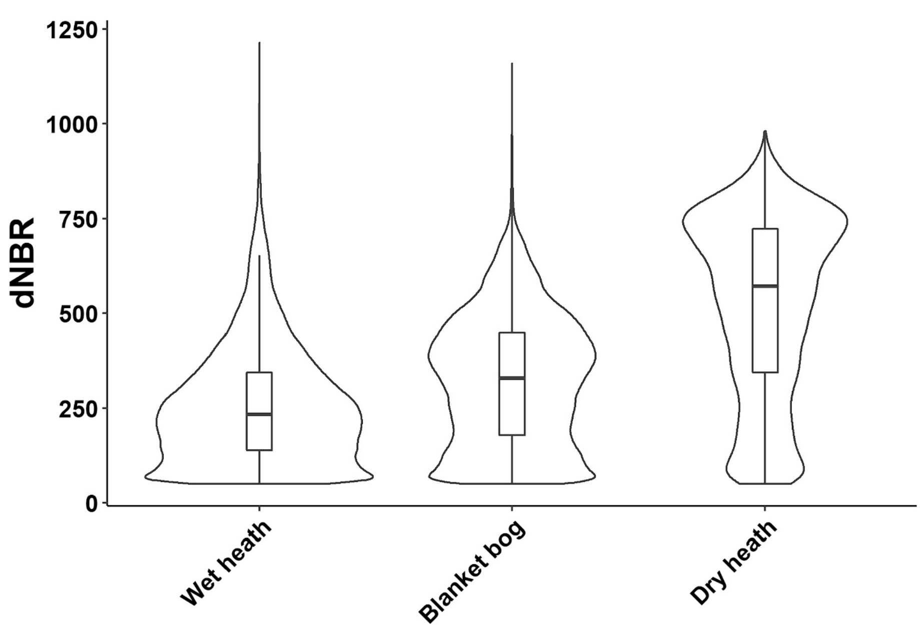

Fig. 3. Violin plot showing the distribution of Differenced Normalised Burn Ratio (dNBR) in wet heath ($N = 462,870$), blanket bog ($N = 355,695$) and dry heath ($N = 26,913$). The boxes represent upper and lower quartiles and median, and the width of the "violin" shape surrounding the box corresponds to the density of data.

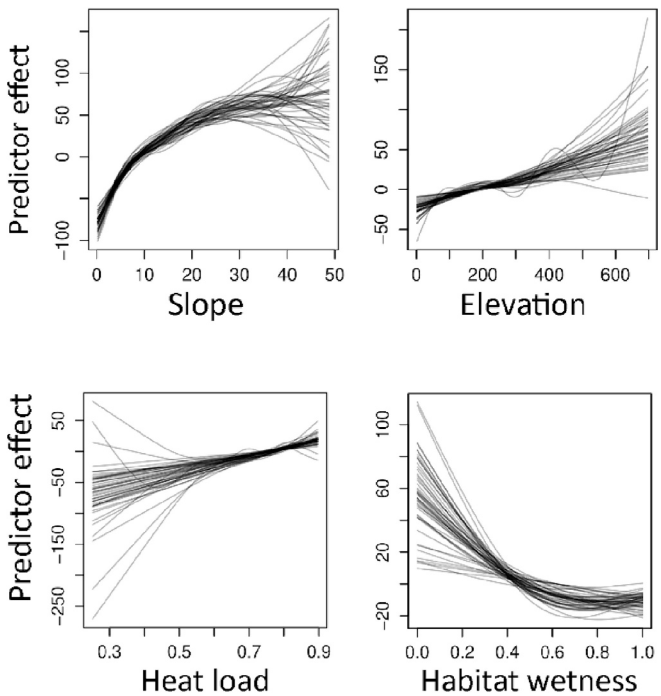

Fig. 4. Results of general additive model of factors affecting fire severity measured as difference Normalised Burn Ratio (dNBR). Lines represent smooth effects of slope (degrees from horizontal), elevation (m above sea level), heat load (solar radiation exposure), wind speed (m s^{-1}) and habitat wetness (0 = dry heath; 0.5 = wet heath; 1 = blanket bog). Lines are overlayed results from 50 repeats of the model, each with random subsets of 50 data points per site.

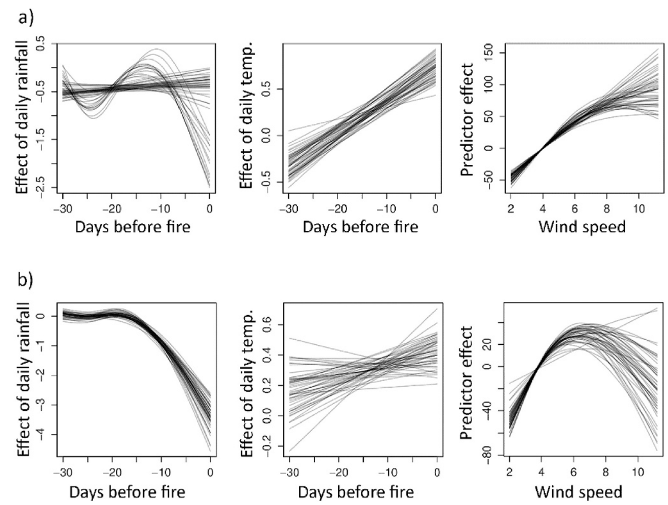

Fig. 5. Results of two versions of general additive models of the factors affecting fire severity measured as difference Normalised Burn Ratio (dNBR). Both models include a spatial exponential correlation effect nested within site (random effect), and (a) includes no other spatial effect whilst (b) additionally includes spatial coordinates as a smoothed, non-nested effect, meaning it considers the geographical distance between fire sites. In both models, lines represent smooth effects of slope (degrees from horizontal), elevation (m above sea level), heat load (solar radiation exposure), wind speed (m s^{-1}), daily rainfall (total mm), daily temperature (mean °C) and habitat wetness (0 = dry heath; 0.5 = wet heath; 1 = blanket bog). The effects of topographical variables and habitat wetness are not shown but were essentially identical as in Fig. 4. Lines are overlayed results from 50 repeats of the model, each with random subsets of 50 data points per site.

positive relationship with severity, whilst the relationship for slopes >40 degrees showed substantial variability, indicating greater uncertainty. Elevation had an increasingly positive effect on severity. Estimates for elevation over 400 m were variable but still consistent. Estimates for low values of heat load were highly variable, and there was an overall increasingly positive effect on severity. The severity levels were comparable between wet heath and blanket bog, but notably higher in dry heath. This was evidenced by a somewhat uncertain but positive effect of low habitat wetness on severity at wetness values <0.4 (i.e., in dry heath), whilst the effect on severity was consistently around or below zero at values >0.5 (i.e., in wet heath and blanket bog). The low certainty (high variability) of estimates for the effects of steep slopes, high elevations, low heat load and low habitat wetness are partly due to a lack of data from areas with these characteristics.

Effects of slope, elevation and heat load from separate models for dry heath, wet heath and blanket bog (equivalent to Model 2 but missing the habitat wetness term) are shown in the Supplementary material (Fig. S3).

When including wind, daily rainfall and daily temperature in the model, we found that the effect of temperature on severity was less uncertain in a model without a spatial smooth term (Fig. 5a), whereas the effect of rainfall was more consistent across resampled data subsets if the spatial smooth term was included (Fig. 5b).

In the model without spatial smoother (meaning, distance between sites was not considered), The rainfall effect smoother was unrealistically complex, whilst temperature consistently showed a trend of a negative effect on severity on days 30 to 20 before fire, which turned increasingly positive from around day 20. Wind had an increasingly positive effect on severity, somewhat uncertain at high wind speeds, most likely due to only one outlier with a wind speed higher than 6 m s^{-1}.

If the spatial smooth term was included (meaning, the distance between sites was accounted for), the effect of daily rainfall on severity was highly consistent and showed no effect on days 30 to 20 before fire and an increasingly negative effect from day 15 to 0. In this model, temperature showed high uncertainty, but still an increasingly positive trend. Wind exhibited a unimodal curve, initially decreasing and becoming less certain at values >6 m s^{-1}, suggesting that both lower and higher than average wind speeds were associated with below-average severity. However, this outcome was likely influenced by the wind speed outlier.

Rainfall, temperature, humidity and VPD at each site on day 0–30 before wildfire, and the resulting fire severity, are shown graphically in the Supplementary material (Figs. S4a-S4d).

Model 6, which included daily 30-day VPD, suggested a complex relationship with severity which was initially positive and turned increasingly negative on days 30 to 20 before fire, and then had an increasingly positive effect on severity from day 15 before fire onset fire (Fig. 6a). The model looking at VPD only on the day of fire onset (Model 7) showed a trend of an increasingly positive effect on dNBR (Fig. 6b).

The GAMMs including CFWIS components, habitat wetness and topographical variables (Models 8a-8f) showed that the effects of almost all CFWIS components on severity were increasingly positive (Fig. 7). The only exception was the effect of FFMC, which followed a more complex pattern and had a negative effect in the highest range of FFMC values. Results for each habitat separately are presented in Fig. S5 in the Supplementary material. In short, DC was the only component which showed a consistent and increasingly positive effect in all habitats when the habitats were analysed separately. BUI worked well for predicting severity in dry heath and ISI worked fairly well in blanket bog, but otherwise, results were quite inconsistent between model repeats. No CFWIS component except for DC was a useful predictor in wet heath.

The R^2 values (mean across model repeats) for all models are presented in Table 4. All models had low to moderate marginal R^2 (fixed terms only) indicating that wildfire severity is unpredictable using the variables in the study, and the relatively high conditional R^2 (fixed terms and random effects) indicated high site-specific variability. A model

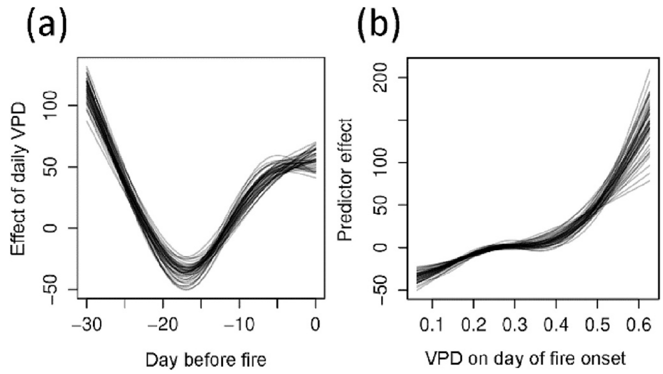

Fig. 6. Results of general additive models looking at the effect of (a) daily vapour pressure deficit (VPD) in the month before fire, and (b) VPD on the day of fire onset, on fire severity measured as difference Normalised Burn Ratio (dNBR). (a) and (b) were two separate models, each including topographical variables (elevation, slope, heat load), habitat wetness and wind speed (the effects of these covariates are not shown but were essentially identical as in Figs. 4 and 5). Lines are overlayed results from 50 repeats of the model, each with random subsets of 50 data points per site. For lagged effects (a), the effect is negative below 0 and positive above 0, whereas for non-lagged effects (b) the effect is relative.

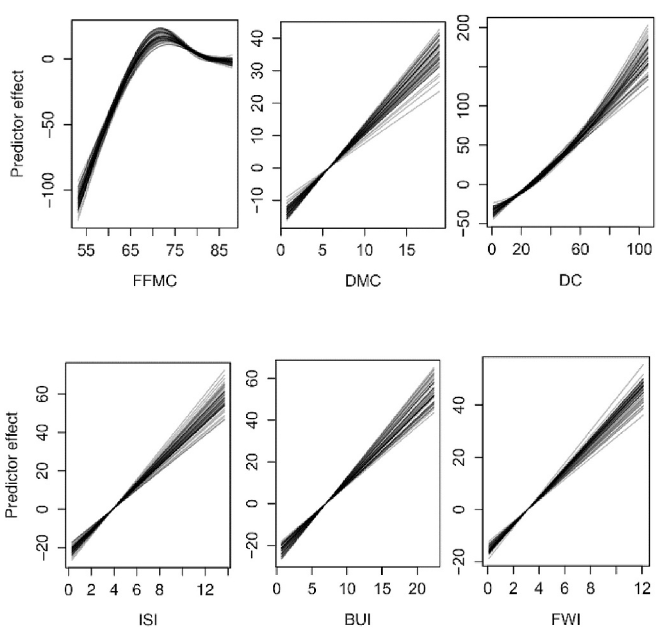

Fig. 7. General additive model results, showing the effects of Canadian Fire Weather Index System components on severity measured as difference Normalised Burn Ratio (dNBR). Slope, elevation, heat load and habitat wetness were included in the models. Each plot is based on a different model. Lines are overlayed results from 50 repeats of the model, each with random subsets of 50 data points per site.

including only spatial terms and the random site effect had a marginal R^2 of only 0.03. Habitat increased R^2 to 0.05, whilst habitat and topography together had an R^2 of 0.19, and adding weather variables to this explained more variance in some cases. Highest R^2 of the assessed models (0.25) was achieved when wind and VPD on day of fire onset were added in addition to habitat wetness and topographical variables. Including DC or BUI instead of VPD also resulted in relatively high R^2.

4. Discussion

In accordance with earlier studies from other regions, we found that

Table 4
R^2 (mean ± SD of 50 model repeats, each with random 50 subsamples) of General Additive Models (GAMs) predicting fire severity measured as difference Normalised Burn Ratio (dNBR). Each row refers to a different model, which included the smooth term(s) named in the row. The models correspond to the ones listed in Table 2 in Methods. All models included a random site effect, a smooth spatial term representing distance between sites and an exponential autocorrelation term of distance between observations within a site. Habitat wetness is a continuous variable where 0 = dry heath, 0.5 = wet heath and 1 = blanket bog. Heat load is a measurement of solar radiation exposure. Fine Fuel Moisture Code (FFMC), Duff Moisture Code (DMC), Drought Code (DC), Initial Spread Index (ISI), Build Up Index (BUI) and Fire Weather Index (FWI) are components of the Canadian Fire Weather Index System.

Model name	Terms included in model	Marginal R^2	Conditional R^2
–	Only spatial terms and random site effect	0.03 ± 0.01	0.29 ± 0.02
1	Habitat wetness	0.05 ± 0.01	0.30 ± 0.03
2	Habitat wetness + slope + elevation + heat load	0.19 ± 0.05	0.48 ± 0.06
3	Model 2 + Rainfall day 0–30 + temperature day 0–30 + wind	0.10 ± 0.02	0.67 ± 0.07
4	Model 2 + Rainfall day 0–30 + temperature day 0–30	0.13 ± 0.04	0.77 ± 0.04
5	Model 2 + Wind	0.17 ± 0.10	0.45 ± 0.11
6	Model 2 + VPD day 0–30 + wind	0.13 ± 0.01	0.98 ± 0.01
7	Model 2 + VPD on day of fire onset + wind	0.25 ± 0.04	0.56 ± 0.06
8a	Model 2 + FFMC	0.14 ± 0.05	0.46 ± 0.05
8b	Model 2 + DMC + wind	0.16 ± 0.04	0.43 ± 0.04
8c	Model 2 + DC + wind	0.21 ± 0.06	0.47 ± 0.07
8d	Model 2 + ISI	0.18 ± 0.09	0.47 ± 0.08
8e	Model 2 + BUI + wind	0.21 ± 0.09	0.48 ± 0.11
8f	Model 2 + FWI	0.19 ± 0.09	0.50 ± 0.08

“bottom-up” effects such as topography and habitat, which influence fuel availability, have a pronounced impact on fire severity compared to “top-down” weather variables (Birch et al., 2015; Estes et al., 2017; Walker et al., 2020). The observed significance may stem from the different scales of the topography and habitat data (30 m) compared to the weather data (8–11 km). The inherent difficulty in aligning dynamic weather effects with specific temporal events contrasts with the static nature of topography and habitat, making the latter more influential in predicting fire severity. The modest explanatory power of our models underscores the intricate and challenging nature of predicting fire severity in upland habitats. This complexity may be attributed to diverse management practices such as prescribed burning, drainage, and variable grazing pressure, impacting fuel load and, consequently, fire spread and severity. The unavailability of precise information on management practices and fine-scale weather hinders model accuracy. Future improvements in models may be achievable with more accurate and detailed data pertaining to management strategies and localised weather conditions.

Our analyses evidenced that wildfire severity differs between upland habitats. Whilst wet heath was the most frequent habitat in our dataset, high fire severity was uncommon in this habitat. Most data points with high severity were located in dry heath, which was a very rare habitat in our dataset, indicating that whilst extremely severe wildfire events are rare in Scotland, dry heath may be particularly susceptible. This is in line with the earlier finding that dry heath experiences lower fuel moisture content and consequently higher fire severity than blanket bog during drought (Grau-Andrés et al., 2018), and with studies on wildfires in uplands which suggest that low severity fire is more common in wet than dry upland habitats (Davies et al., 2016, 2023). The negative effect of habitat wetness on fire severity can be linked to the differences in vegetation composition between habitats, which may explain how wildfires in wet habitats can be large but of low severity. Wet heath and blanket bog typically have a high proportion of *Sphagnum* mosses and graminoids compared to dry heath, and lower proportion of feather mosses and shrubs such as *Calluna vulgaris*. *Sphagnum* mosses retain moisture far more efficiently than feather mosses, potentially contributing to the lower susceptibility to high fire severity observed in wet heath and blanket bog ecosystem (Terrier et al., 2014). Graminoids ignite at higher fuel moisture content levels than shrubs, and this effect is particularly pronounced in dead graminoid fuel (Santana and Marrs, 2014, 2016). Purple moor grass (*Molinia caerulea)* is very abundant in Scottish wet heath and this deciduous grass retains last year's dead foliage, resulting in a high proportion of dead fuel, particularly in spring (Santana and Marrs, 2016). The dead grass leaves may sustain ignition and fire spread even during conditions when the *Sphagnum* moss and peat have sufficient fuel moisture content to resist ignition (Santana and Marrs, 2016). A similar pattern can be expected with other graminoids characteristic of wet heath and blanket bog, such as the cotton sedges *Eriophorum vaginatum* and *E. angustifolium* (Santana and Marrs, 2016). Furthermore, habitats characterised by a higher ratio of shrubs to graminoids, such as dry heath, are prone to experiencing elevated fire severities due to the abundant fuel provided by shrubs compared to graminoids (Taylor et al., 2021), resulting in fires being sustained for longer. These variations in vegetation composition may account for the occurrence of low severity wildfires in wet heath and blanket bog, whilst high severity fires are more common in dry heath.

UK peatlands hold an estimated 2300 Mt. of carbon, with the majority being stored in Scottish blanket bog (Billett et al., 2010; Chapman et al., 2009). Despite only 6 % of burnt blanket bog area in our study being affected by very high fire severity (dNBR in the 95th percentile of the whole dataset), this still amounts to approximately 1000 ha due to the extensive total burnt area in blanket bog. In comparison, 46 % of burnt dry heath was affected by very high fire severity, but this equates to a comparatively low 620 ha. High severity fires in blanket bogs are particularly concerning as they are susceptible to smouldering peat fires, releasing substantial carbon into the atmosphere (Turetsky et al., 2014). Consequently, wildfires pose a significant threat to carbon stores in deep peat of blanket bogs, despite the rarity of high fire severity in wet habitats.

The positive correlation between slope and severity found here was most pronounced at moderately steep slopes, whilst predictions at slope > 30 degrees were highly uncertain, which is very similar to findings by Estes et al. (2017) in northern Californian forests. A speculative explanation for this is the high ratio of bare rock to vegetation at very steep slopes, which may result in low fuel load and therefore low probability of fire spread. Whilst slope has repeatedly been found to have a positive effect on fire severity in different ecosystems (Birch et al., 2015; Costa et al., 2011), the effects of aspect-related variables such as heat load may be dependent on climate and habitat. A positive correlation between heat load and severity, as found here, can be expected in humid, treeless ecosystems where flammability is limited by fuel moisture content. The opposite has been found in forest or Mediterranean ecosystems, possibly because flammability is instead limited by fuel load, which may be lower on sunny slopes where plant growth is impaired due to low water availability (Birch et al., 2015; Estes et al., 2017).

Wind had a pronounced positive effect on severity, which may be due to the reduced angle of the flame to the substrate, leading to predrying of fuel in a similar manner to slope (Costa et al., 2011). Here, we did not examine the interaction of wind direction and slope aspect which may have higher explanatory power, since up-slope wind may theoretically result in higher severity than down-slope wind (Costa et al., 2011). However, wind-aspect alignment has previously been found to be a poor predictor of fire severity (Birch et al., 2015). Wind can impact the rate of spread of a fire which can result in larger fire area (Davies et al., 2009) and our results suggest that wind may be an important predictor of severity as well.

Whilst rainfall and air temperature in the month before fire showed expected patterns (increasingly negative effect of daily rainfall and increasingly positive effect of daily mean temperature), the effects were less apparent than for wind and topographical variables, again, partly because of the difference in spatial scale. The fact that slight changes in the models, such as inclusion or exclusion of a spatial smooth effect, changed the outcomes of the rainfall and temperature effects, suggests that the estimates of the effects of these variables are sensitive and effects may be easily confounded. Nevertheless, the models indicate that fire severity is affected by the length of the period of dry, warm weather preceding the fire, cumulatively for up to 15 days prior to fire and with an increasing influence as time approaches fire onset. This may either suggest that longer periods of drought (> 15 days) are rare in Scotland, or that a drought longer than 15 days does not further increase fire severity. If the former is true, climate change and longer periods of drought may result in an increased severity of wildfires.

Summer mean VPD has been shown to be a strong predictor of wildfire severity, area and occurrence in studies with a large temporal and spatial scale (Grünig et al., 2021; Jain et al., 2022; Mueller et al., 2020). In accordance with this, we saw a positive effect of VPD on fire severity on the day of fire and in the 10 days preceding fire onset. Effects of VPD on severity further ahead of time than 10 days were unintuitive and could be the result of complex relationships between VPD and interactions of humidity, temperature and rainfall, which can make the predictive value of VPD decrease with increasing lags. If the positive effect of VPD on approximately days 30–22 before fire is depicting a real ecological relationship, it may be related to low humidity during cold weather in winter and early spring, as majority of wildfires in Scotland occur in April. Cold and dry weather may inhibit water uptake or cause tissue damage in vegetation and therefore result in reduced fuel moisture content or increased dead fuel load (Davies and Legg, 2008).

Whilst VPD outperformed any component of the Canadian Fire Weather Index System (CFWIS) in terms of explanatory power, the Drought Code (DC) was the CFWIS component which exhibited the most consistent relationship with severity. While DC effectively predicted severity both when habitats were analysed together or individually, the Build Up Index (BUI) also emerged as a decent predictor of severity in dry heath. DC is integrated into the calculation of BUI, and both indices summarise the moisture content of soil layers at depths >10 cm, correlating with fire behaviour characteristic of high severity, such as smouldering (Davies et al., 2013, 2016). In contrast, Fine Fuel Moisture Code (FFMC) showed least usefulness in predicting fire severity. This component summarises the moisture content of fine fuels and is associated with ignition risk and therefore wildfire occurrence rather than severity (Davies, Domènech, et al., 2016; Davies et al., 2013; De Jong et al., 2016; Taylor et al., 2021). The very low correlation between FFMC and severity may furthermore be due to differences between ground fuels in British upland ecosystems, dominated by mosses, and Canadian boreal forests floors, abundant in pine needles, which the CFWIS was originally developed for (Taylor et al., 2021; Van Wagner, 1974).

4.1. Limitations and uncertainties

Our study relies solely on remotely sensed data, which are comparable across sites and provide a reasonable estimate of relative severity. Inevitably many wildfire events were excluded from the analysis due to high cloud cover, which limited the size of the data set. Both the accuracy of estimation of severity, and the number of sites included, could have been strengthened with on-site measurements from all recently burned areas. However, due to the stochastic occurrence of wildfire, this would be a logistically challenging approach, requiring a longer-term study to encompass sufficient fires. Cloudy conditions also caused variability in the time interval between useable satellite images before and after a fire, which may introduce some uncertainty in the accuracy of our dNBR measurements.

4.2. Implications for management

Since a large proportion of dry heath in Scotland is managed with prescribed burning to provide habitat for game birds, the CFWIS system may be a useful tool for land managers during the prescribed burning season. However, our study evidenced that individual CFWIS components, particularly DC, are more strongly related to fire severity than the final index of the CFWIS. Burning during days of low index values, particularly DC, may reduce the risk of prescribed fires of higher severity than was intended, whilst high DC together with high wind speeds may increase risk of uncontrolled fires. Further research to develop a fire danger rating system specifically for Scotland, based on both wildfire occurrence and severity, is needed to increase certainty of predictions of wildfire risk and suitable weather for prescribed burning.

5. Conclusions

In conclusion, topography, habitat type, and weather shape wildfire severity in Scottish uplands, yet estimating their relative importance is challenging due to spatial scale differences. The study highlights that whilst blanket bog and wet heath account for the majority of burnt areas in Scotland, these fires tend to be of low severity. In contrast, dry heath only constitutes a small proportion of burnt area but the mean severity is markedly higher. Despite the relatively low proportion of very severe wildfires (dNBR in the 95th percentile) in blanket bog, they still encompassed at least 1000 ha between 2015 and 2020, posing a potential threat to peatland carbon stores. Our findings highlight the increased risk of severe wildfires in wet upland habitats during prolonged periods of dry, warm weather, emphasising the impact of climate change on wildfire susceptibility.

CRediT authorship contribution statement

Noemi A.L. Naszarkowski: Writing – original draft, Visualization, Project administration, Methodology, Investigation, Formal analysis, Data curation, Conceptualization. **Thomas Cornulier:** Writing – review & editing, Writing – original draft, Visualization, Methodology, Formal analysis, Data curation. **Sarah J. Woodin:** Writing – review & editing, Supervision, Methodology, Formal analysis, Conceptualization. **Louise C. Ross:** Supervision, Methodology, Conceptualization. **Alison J. Hester:** Writing – review & editing, Supervision, Methodology, Conceptualization. **Robin J. Pakeman:** Writing – review & editing, Supervision, Project administration, Methodology, Funding acquisition, Formal analysis, Conceptualization.

Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

Data availability

Data will be made available on request.

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Appendix A. Supplementary data

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