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Characterizing the Rate of Spread of Wildfires in Emerging Fire Environments of Northwestern Europe

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Abstract. *In recent years fires of greater magnitude have been documented throughout northwest Europe, and with several climate projections indicating future increases in fire activity in this temperate area, it is imperative to identify the status of fire in this region. This study unravels important unknowns about the state of the fire regime in northwest Europe by characterizing one of the key aspects of fire behavior, the rate of spread (ROS). Using an innovative approach to cluster VIIRS hotspots into fire perimeter isochrones to derive ROS, we identify the effects of land cover and season on fire rate of spread of 254 landscape fires that occurred between 2012 and 2020. Results reveal no significant differences between land cover types and there is a clear peak of ROS and burned area in the months of April and May. During this late spring period, 67% of the burned area occurs and median fire runs are approximately 0.16 km/hr during a 12 hour overpass. Heightened ROS and burned area values persist in the bordering months of March and June suggesting that may present the extent of the fire season in northwestern Europe. Accurate data on ROS among the represented land cover types as well as periods of peak activity are essential for determining periods of elevated fire risk, the effectiveness of available suppression techniques as well as appropriate mitigation strategies (land and fuel management)*.

1. Introduction

Wildfires are among the most common natural disturbances across the globe and play a key role in shaping many ecosystems. In recent years fires have had an emerging impact in areas not traditionally considered fire prone such as the temperate region of northwest Europe. While fires in these regions were once considered an anomaly, in recent years the occurrence of fires of greater magnitude has been increasing (San-Miguel-Ayanz et al., 2021). In 2020, the Netherlands experienced its potentially largest wildfire in recent history, affecting 710 hectares in the nature reserve of Deurnese Peel (Stoof et al., 2020). In the same vein, the United Kingdom had consecutive record fire seasons in 2018 and 2019 with burnt areas of 18,032 ha and 29,152 ha, respectively, the largest burn area in the past 10 years (Belcher et al., 2021). Several climate projections suggest increased fire activity in northwestern Europe in the future due to projected drier and warmer weather (Krawchuk et al., 2009; Lung et al., 2013; de Rigo et al., 2017). Moritz et al. ((Moritz et al., 2012) identified that temperate forests and grasslands are among the most vulnerable biomes at the mid to high latitudes to increases in the probability of wildfires especially in the last quarter of the 21st century (2070–2099). Despite the projected elevated risk, fire behavior within this ecosystem is not well understood. Influential drivers such as vegetation and moisture conditions vary considerably from other parts of Europe such as the Mediterranean where fire and ignition conditions are better researched and understood.

Fire regimes are defined as long-term patterns of frequency, intensity, and fuel consumption of wildfires in a given area (Keeley et al., 2011). Anticipated changes in local climate are likely to drive alterations in fuels (types, structure, and heterogeneity) as well as conducive fire weather and thus fire occurrence and behavior. Temperate ecosystems, such as those in northwest Europe, which tended to have had limited fire exposure, may become increasingly fire-sensitive and susceptible to increases in fire frequency (McWethy et al., 2013; Kitzberger et al., 2016). Given that fire sensitivity is strongly dependent on interactions between vegetation phenology and fire seasonality, accounting for these factors is imperative when looking at fire behavior (Miller et al., 2019). Timing of phenological events is a major determinant of fuel availability and flammability and within temperate landscapes appears to be driven by changes in temperature (Fares et al., 2017; Chuine and Cour, 1999). The “green up” is likely an important phenological stage when it comes to fire behavior as this is when sap flow begins increasing vegetation moisture. Prior to this green up period, vegetation is drier and may be more susceptible to ignition as fuel moisture is among the most critical parameters affecting fire ignition and propagation (Parsons et al., 2016). *Calluna vulgaris* for example, a shrub commonly found in heathlands, is subject to extremely low fuel moisture levels in early spring as roots still frozen from winter dormancy limit water uptake, posing elevated ignition risks (Davies et al., 2010). Among the different aspects of fire behavior, the rate of spread (ROS) is a key indicator for characterizing fire regimes as it directly contributes to fire size and the overall residence time of the fire (Gill et al., 2008). Forest and fire management depend on accurate knowledge of fire behavior and, particularly, ROS for assessing appropriate fuel treatments (Vaillant et al., 2009). Furthermore, emergency responders such as firefighting operations strongly rely on accurate ROS data to determine their initial and extended attack as well as their fire suppression capabilities. Fires with lower spread rates are generally able to be attacked at the head using hand tools; however, those with higher spread rates will often be more intense and would require special equipment such as dozers and retardant aircraft to be effective (Andrews, 2011). Accurate information on the rate of spread of fires can therefore help increase preparedness of land managers and emergency services across the region.

The relative novelty of fire in northwest Europe means that classifying a fire regime is rather difficult due to the scarcity of data and inconsistencies among record keeping (San-Miguel-Ayanz et al., 2021). European countries vary in their national classifications of fire, the quality of their fire-cause investigations, and the length of time of national databases (Tedim et al., 2015; Fernandez-Anez et al., 2021). Moreover, national fire databases tend to include data on fire occurrence and cause, but not on fire behavior. Fortunately, remote sensing methods, through the use of satellites, provide spatially and temporally consistent data to permit further analysis of fire behavior, particularly ROS (Sá et al., 2017; Benali et al., 2016). Several studies have proposed methods to extract ROS from satellite imagery using various sensors, such as the Advanced Very High Resolution Radiometer (AVHRR)

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(Chuvieco and Martin, 1994; Al-Rawi et al., 2001). Several authors have turned to satellite thermal imaging from MODIS (Moderate Resolution Imaging Spectroradiometer) to reconstruct fire progression for larger fires throughout the world (e.g., (Loboda and Csiszar, 2007; Veraverbeke et al., 2014; Jin et al., 2015)). Liu et al. (Liu et al., 2018) employed the Himawari-8 geostationary satellite to extract the ROS in near real time from grasslands in Australia with promising results. The application of active fire detection products for identifying ROS has the potential to calibrate and validate fire spread models, and several studies have successfully demonstrated methodologies for rapid accurate assessments of ROS in near real time (Sá et al., 2017; Cardil et al., 2019). Many of the aforementioned methodologies and the sensors implemented have been applied in regions where fires tend to be much larger than in temperate Europe, such as in the Mediterranean, California, or Australia (Andela et al., 2019). Our study relies on the Visible Infrared Imaging Radiometer Suite (VIIRS) satellite, which features a higher spatial resolution of 375 m for active fire detection (as opposed to 1 km for MODIS) and may capture more of the smaller fires prevalent in a temperate region.

The objective of this study was to characterize the rate of spread of landscape fires within a temperate region facing an increasing risk of wildfires, namely Northwestern Europe. We developed a new methodology to derive the rate of spread from hotspots from the VIIRS active fire data product because of its global coverage, near real-time accessible data, and improved spatial and temporal resolution compared to MODIS (Schroeder et al., 2014). Subsequently, we assessed the effects of season and land cover type on rate of spread, as well as differences between countries. A thorough understanding of fires in these emerging regions of northwest Europe will be imperative in developing functional fire management strategies and will serve as a baseline to assess future impacts of climate change.

2. Materials and Methods

2.1 Study area

For the purpose of this study, the boundaries of northwest Europe were defined by the northern Atlantic Biogeographical region (above 49th parallel), and includes many of the traditionally wet countries such as the United Kingdom, Ireland, the Netherlands, Belgium, and Denmark (Fig. 1) (Sundseth et al., 2009). The Atlantic Biogeographical region is distinguished by an oceanic climate and occupies much of the flat lowlands along the Atlantic coastline. Overall the climate is temperate, marked by its mild winters and cool summers with westerly winds and moderate rainfall throughout the year (Sundseth et al., 2009). The landscape tends to be intensely managed with considerable agricultural areas and expansive industrial and urban regions (Feranec et al., 2010). Nature environments are often isolated and discontinuous due to interwoven urban development spurred by dense populations. The represented vegetation types are diverse and feature heathlands, broadleaf beech forests, meadows, and peat bogs among many others. The ocean drives the climate in this region and as a result it is typically wet and humid for much of the year.

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2.2 Visible Infrared Imaging Radiometer Suite (VIIRS) Data

We used data from the Visible Infrared Imaging Radiometer Suite, a satellite active fire data product widely used in fire modeling applications, in part because of its higher spatial and temporal resolution compared to other satellites such as MODIS. NASA's VIIRS was launched aboard the Suomi-National Polar-orbiting Partnership (S-NPP) satellite in October, 2011 and has since been providing consistent coverage approximately every 12 hours (Schroeder et al., 2014). Among VIIRS's greatest strengths is the ability to detect at moderate 375 m spatial resolution (Oliva and Schroeder, 2015); making it an ideal instrument for detecting the smaller fires we anticipated in our study area. VIIRS hotspot data were collected from the NASA Fire Information Resource Management System (FIRMS) portal (https://firms.modaps.eosdis.nasa.gov/) for the period of January 20th, 2012 to June 1st, 2020 as no earlier data was available.

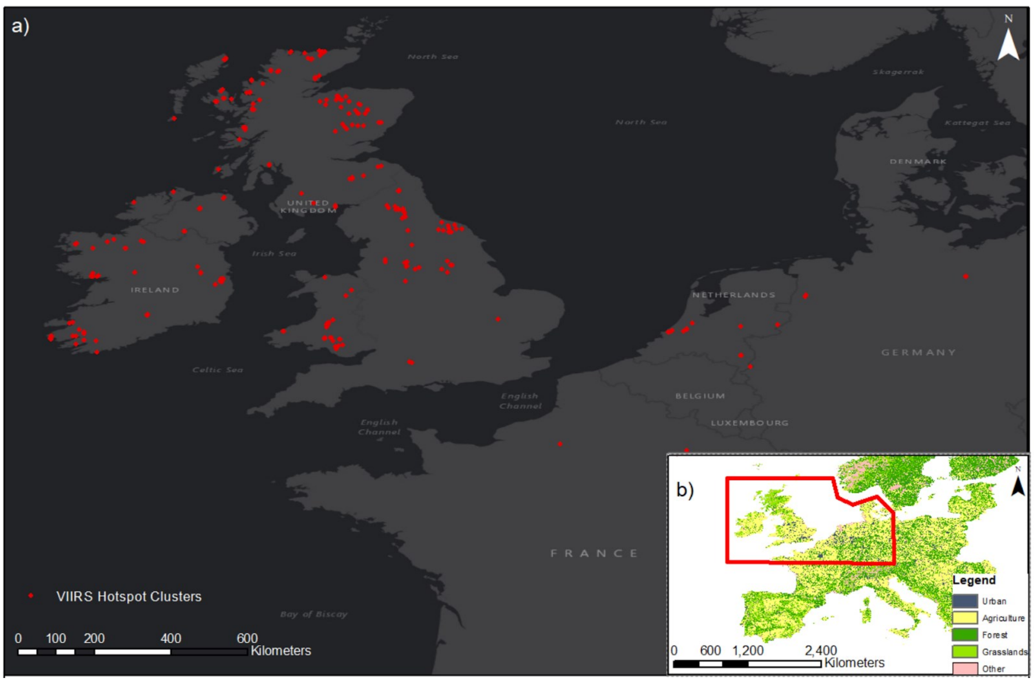

Figure 1. Study area of northwest Europe. a) Locations of the fire hotspot clusters from VIIRS 375 m active fire product derived from 344,000 hotspot detections from January 2012 through June 2020. b) VIIRS hotspots retrieved from the area of interest, highlighted in red, encompassing the United Kingdom, Ireland, the Netherlands, Belgium, Denmark, and parts of Germany and northern France.

2.3 Clustering VIIRS data by fire incident based on space and time

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VIIRS detections are points scattered in time and space. Developing ROS vectors involves clustering the hotspots so that each grouping represents a fire incident. The clustering is a three step process: 1) clustering in space, 2) clustering in time within each previous space cluster, and 3) filtering out clusters with less than 20 VIIRS hotspots, as these are insufficient to derive ROS. The clustering in space was carried out first using a grid-based algorithm with the hotspots being reprojected onto a 5 km raster, and neighboring cells containing hotspots were merged to define a cluster area. This technique was chosen because it is much faster than other hierarchical algorithms and does not require a predefined number of expected clusters. This method is intended to assure that any hotspot in a cluster is less than 14 km away from its closest neighboring hotspot in order to properly distinguish different fire incidents. This cutoff distance was determined as the farthest possible distance of two points in neighboring cells with a cell size of 5 km, due to the limitations of the reprojected raster grid resolution. The clustering in time was conducted by ordering the space clusters by time and creating divisions or break points if there was a time difference greater than 48 hours in between consecutive points. The chosen threshold values for the clustering and filtering are heuristic and could be slightly modified without significant changes in the final result. Pre-analysis, these threshold values were adjusted to optimize the balance between the number of fires detected without sacrificing the larger widespread events.

2.4 Generating fire perimeters and ROS vectors

Once the hotspots were classified into individual fires the next step was to generate fire perimeters at each timestep for each fire based on the satellite overpass. All hotspots at any given time step were merged into a single polygon through a Delaunay triangulation method between the points. Hotspots were merged to ensure that the perimeters were formed using the total burned area and not only the active part of the fire at that time step. This triangulation method is closely related to Voronoi diagrams and has the important properties of not having intersecting edges, defining triangles with the three nearest existing points, and reducing the number of possible linking lines between points. From the initial Voronoi mesh, an α-Shape algorithm was applied to filter out triangles whose circumradius (radius of circle circumscribed in a triangle) was greater than the stated α alpha value. This process splits the original mesh into independent fires if they are sufficiently distant from each other and creates unburned areas inside fires.The value of α determines the porosity of the final shape, a high value will lead to a well-known convex hull, while a lower value will increase the number of edges and the number of independent perimeters. In this case, α was heuristically set to be 1 km. To obtain only the outer edges of the perimeters, all edges shared by two triangles were removed from the set. Remaining triangle edges were then ordered into a continuous line and converted into a polygon geometry with its external and internal boundaries.

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Figure 2: Example of multipolygon feature for the Souain fire in northern France. Green polygon indicates the fire extent at first satellite overpass a) while yellow polygon indicates fire growth at second overpass. b) Rate of Spread (ROS) vectors are shown between the two fire extents with the max ROS highlighted in red.

With the fire progression multipolygons developed, the rate of spread vectors could be calculated. For each vertex of the polygon at time *t+1* the closest vertex of the parent polygon at time *t* was identified. Taking into consideration the distance and time between both polygons, we calculated the ROS of each spread vector (Fig. 2). To increase the accuracy of the spread vectors, the number of vertices at each polygon and time step was increased by linear interpolation between neighboring points.

2.5 Omission of False Detections

VIIRS sensors detect fires through the identification of mid-infrared radiation emitted from heat sources across the landscape. As these hotspots may also include heat coming from other sources (such as gas flares at industrial sites), it was necessary to screen the derived ROS clusters for false detections. As part of this process we overlaid the polygons on the Copernicus Land Monitoring Service's Corine Land Cover Map 2018 ((2019a)) to distinguish landscape fires from other heat sources such as active volcanoes, artifacts of heated plumes, or a myriad of other anthropogenic phenomena. Polygons identified within a 1 km boundary of land cover classified as urban or industrial were excluded from the database.

2.6 ROS Classification and Analytical Methods

Each individual fire contained many vectors for ROS at each vertex for each timestep representing the fire progression in every direction. In order to identify the widely utilized head of the fire we grouped vectors by fire and timestep and filtered out the maximum ROS value for each fire. As each timestep also featured data on land cover, country of origin, and the month of incidence it became possible to draw comparisons between variables. There were some issues within the clustering process that permitted fires with greater distances to be classified as an individual event, which led to erroneous extreme ROS rates. To account for this, all extreme spread vectors were checked manually for mistaken groupings and if identified as such excluded from the dataset. Remaining VIIRS ROS vectors were then grouped by their associated country, land cover, and month to determine the effects of season and land cover on fire spread using an ANOVA and Tukey statistical analysis.

3. Results

3.1 Distribution of fire detections and classification of fire events

The 344,048 individual fire detections identified in our study area were grouped into 2,543 clusters, of which 254 were verified to be "real" landscape fires and not as an artifact of permanent hotspots or thermal plumes. The greatest number of fires was registered in the British Isles while detections were scarce in continental Europe. There were no fires registered for the study period in Belgium or Denmark. The final output for each fire included: the timing of the fire, the burnt area, the land cover, and the maximum ROS.

3.2 Burnt Area

Peak burn area across the study region occurred in the months of April (43%) and May (24%) when 67% of the total burnt area was observed (Fig. 3a). In March there was a greater percentage of fires (23%) compared to May (13%) although they contributed to a smaller percentage of overall burnt area, indicating that while fires in March may be more frequent they are also smaller. There was a second smaller peak of increased burnt area in July consisting of fires from 2018, which amounted to nearly 14% of total burned area (Fig. 3a). In terms of fire size, nearly 80% of the burned area was caused by wildfires between 1-10 km^2 (Fig. 3b). These mid-sized fires comprised half of the total fires detected. Fires exceeding 10 km^2 made up approximately 13% of the total burnt area but only 2% of total wildfires. On the other hand, fires less than 0.01 km^2 were rarely detected with our satellite-based analysis, comprising approximately 0.002% of the total burned area and 1% the total number of fires. Fires between 0.01–0.1 km^2 were also seldom observed with 0.3% of the burnt area set by 10.2% of total fires.

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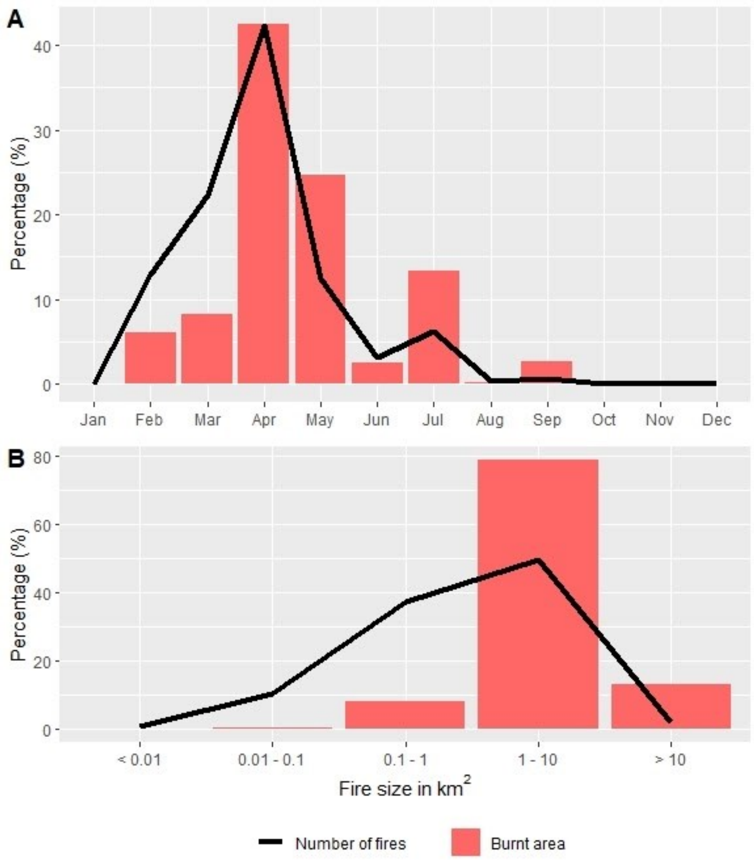

Figure 3: Burnt area percentages for northwest Europe calculated a) monthly and b) according to size distribution.

3.3 Effect of Season on Rate of Spread

Trends for the northwestern European area indicated that the months of April and May witness the most active fire activity (Fig. 4a). It was during this period that the median ROS was the greatest (0.15 km/hr and 0.12 km/hr, respectively), and this was reflected in the greater burned area, exceeding 500 km^2 for both months (Fig. 4a). ROS in March also registered quite highly with a median of 0.11 km/hr. The remaining months of February, June, July, and September featured a median ROS of 0.068 km/hr. Mean ROS within northwest Europe was approximately 0.19 km/hr for the entire study period, with half of our ROS observations falling within the 0.04 km/hr to 0.28 km/hr range (Fig. 4a). The data revealed that for the fires considered, 12-hour spread rates rarely exceed 0.5 km/hr. Fires at the tail ends of this timeframe in August and September registered among the lowest spread rates comparatively, and this is reflected in the reduced accumulated burn area of around 100 km^2 in these two months (Fig. 4a).

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Zooming into the country level, across northwest Europe landscape fires were detected for the months of February to September, predominantly in April and May (Fig. 4b). Peak ROS for England, Ireland, Scotland, and Northern Ireland was found in the late spring and earlier summer months. The Netherlands and northern France only detected fires in a single month but they both tend to match the trend. The seasonal patterns observed for both Wales and Germany appear to deviate from this trend. Germany reached its peak ROS in February and further fires were not detected by VIIRS until the end of summer months in July and September. Furthermore, the ROS captured in February was the highest recorded at 1.4 km/hr. Wales, like Germany, reached its highest ROS in February but the values were not all that different in the following months.

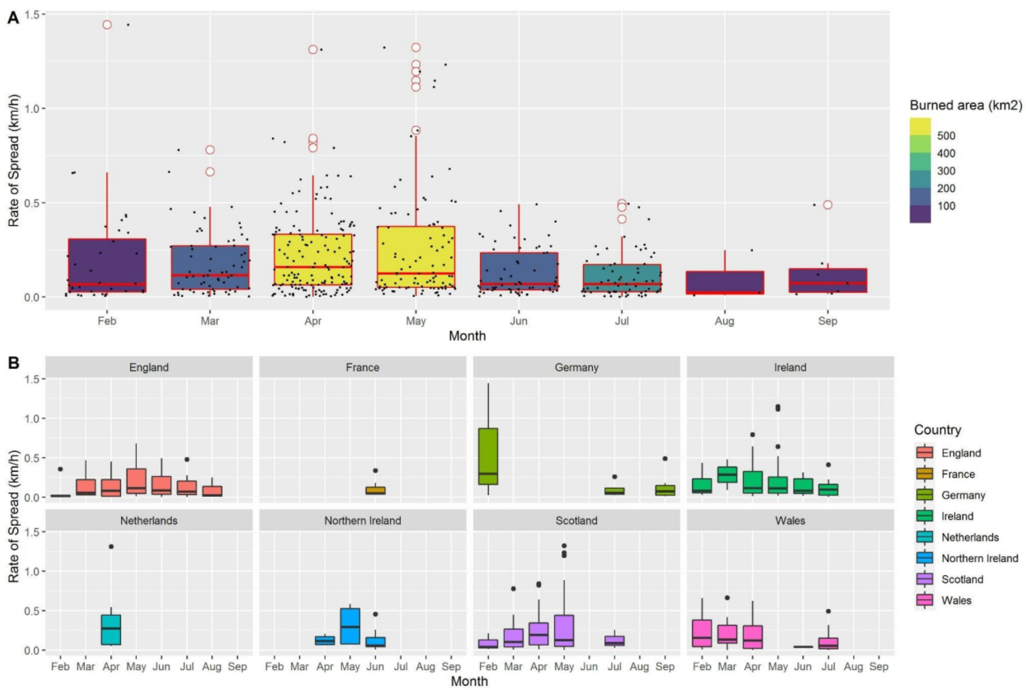

Figure 4: Rate of spread for northwest Europe from 2012–2020 calculated monthly a) for the northwest European area with the total burn area indicated in color, the points represent sample size, and b) per country. Fires were not detected for months not represented in the figure.

3.4 Land Cover Effects on Rate of Spread

Statistical analyses did not reveal statistically significant effects of land cover on ROS (p=0.13). Differences between land cover types were small, with a mean difference of approximately 0.13 km/hr between the highest and lowest land covers (Fig. 5) Peat bog vegetation showed the greatest mean ROS at approximately 0.21 km/hr. On the other end of the spectrum were the mixed forests with a mean spread rate of approximately 0.077 km/hr and pastures at 0.1 km/hr. Coniferous forest, transitional woodland-shrub, and natural grasslands all exhibited similar mean

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spread rates of approximately 0.12 km/hr. Moors and heathlands, broad-leaved forest, and land principally occupied by agriculture, with significant areas of natural vegetation, all featured mean ROS on the higher end of the scale ranging from 0.15 to 0.175 km/hr (Fig. 5).

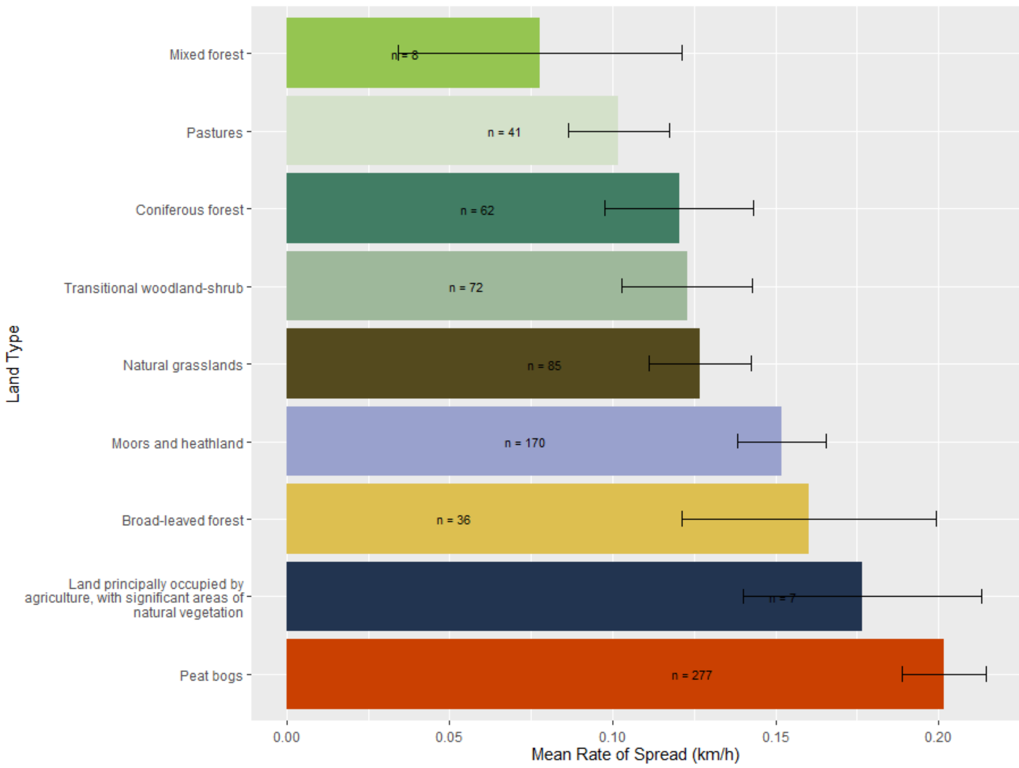

Figure 5: Rate of Spread across various represented land covers in northwest Europe.

4. Discussion

4.1 Burned Area & Peak Activity

The analysis of the intra-annual burned area is essential for determining periods of peak fire risk and impacts. Our results clearly indicate a major peak in burnt area in spring (April and May) but also a second minor peak in mid summer (July) (Fig. 3a). This secondary peak in July was composed entirely from fires in the UK during 2018, a summer in which there was extensive drought and heatwave across northern Europe (Fu et al., 2020). Summer fires are unusual as they occur following the spring green up period when the vegetation moisture is typically high, hence large fires in temperate summer tend to require considerable arid conditions or drought. Regarding fire size, our analysis identified that most of the burned area was contributed by fires between 1–10 km^2 with slight contributions

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from fires in the 0.1–1 km^2 and >10 km^2 scales. This indicates that mid to large size fires are responsible for most of the total burned area rather than smaller fires. The lack of fires smaller than 1 km^2 can likely be explained by the fact that the VIIRS satellite was unable to capture fires of this magnitude due to limitations of the temporal and spatial resolution. Smaller fires are much more ubiquitous than larger fires as fire size distribution commonly follows the power-law function (Cui and Perera, 2008; Hantson et al., 2015). While it is likely that these smaller fires are more frequent than indicated, fires of this scale are less likely to be significant contributors to overall burned area (San-Miguel-Ayanz et al., 2021). Moving forward, it is important to consider that the fires included in this study are of mid to large size rather than smaller fires especially when it comes to estimating the ROS as smaller fires are likely to reduce the mean ROS.

Of the 254 fires considered in this study, It is unlikely that any were prescribed burns as most of the fires accounted for were outside the main prescribed burn window of October to March. Moreover, all of our fires burned overnight and prescribed burn codes in the study region do not permit burning overnight ((Heather and grass burning: rules and applying for a licence, 2021; Guidance - The Muirburn Code, 2021; Department of Agriculture, Food and the Marine, 2021)). Furthermore, our clustering algorithm required a minimum of 20 hotspots to be identified as a potential fire, which is unlikely for a prescribed burn.

4.2 Spread Rates & Peak Activity

Spread rates were calculated for various countries throughout the year and for various land covers in a region where fire behavior data tend to be scarce with a limited history of records. The seasonal rate of spread analysis indicates peak burn area and ROS in the months of April and May (Fig. 3 & 4). The bordering months of March and June also featured heightened rate of spread and burnt area values suggesting that March through June may present the extent of the peak fire season in northwest Europe. The fire season is likely longer than indicated within our study but due to sensor limitations we are unable to capture and account for the smaller fires and can only ascertain periods of peak activity of the larger fires. While studies on fire regimes within this region are scarce, the timing and duration of the peak of fire season outlined in our study is in agreement with the fire season set out in various literature. De Jong et al. (de Jong et al., 2016) concluded that a majority of wildfire activity in the United Kingdom occurs from March to May (59% of events and 95% of the burn area). Likewise, the Irish Department of Agriculture, Food and Marine (DAFM) distinguishes the period of heightened fire risk from the months of March to June (Fire Management, 2021), and within the Netherlands, peak fire activity is typically in the spring and early summer (April to June) (San-Miguel-Ayanz et al., 2019)

The March–June spring fire season identified in northwest Europe is a clear contrast to the Mediterranean fire season, which features a minor peak in spring but a stronger peak towards the months of July–September, at the later end of summer (Pausas and Paula, 2012; Le Houérou, 1973). The Mediterranean fire peak culminates in summer as the fuel moisture is lowest during this period within this climate (Chéret and Denux, 2007). However, this likely

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differs in northwest Europe where the temperate climate is typically wetter and more humid in summer and the period of lowest fuel moisture tends to fall before the phenological green up period in late spring. Davies et al. (Davies et al., 2010) reviewed temporal variations in moisture for *Calluna vulgaris* across Scotland and identified consistently low live fuel moisture contents in spring and consistently high moisture contents in summer which were largely attributed to the flush of young green summer growth. Davies et al 2010 also noted that vegetation moisture might be more sensitive to changes in weather conditions than seasonal trends considering the rapidity of changes therefore combinations of low nighttime temperatures, frozen ground, and relatively warm sunny days in the early spring may lead to elevated fire hazards. Significant correlations have been widely observed between wildfires and the phenological stages of vegetation across southern Europe (Moreira et al., 2009; Angelis et al., 2012), it is possible that local phenology plays a role in the differences in peak fire activity in northwest Europe. The phenological cycle alters key characteristics of fuels including biomass, spatial distribution, moisture content and chemical composition, which are key determinants for fire behavior (Fares et al., 2017). Further research is needed to identify linkages between vegetative phenology, meteorological conditions, and fire occurrence in this region.

4.3 Effect of Land Cover Type

Surprisingly, our study did not yield any significant effect of land cover on ROS. Land cover has been shown to be among the main drivers of fire intensity and ROS through its influence on plant biomass, vegetation structure, and moisture content (Moreira et al., 2009). In a similar study, Loboda and Csiszar (2007) reconstructed fire spread across Eurasia using MODIS and derived ROS and found significant effects of ecoregions. However, ecoregions are of greater spatial scale and do not account for the finer distribution of different vegetation types. Future studies could benefit from the use of high resolution fuel maps, which were not yet available at this time, rather than coarse land cover when investigating links to ROS. Land cover may not be able to sufficiently encompass the complexity of fuel types present. Perhaps a reason for the lack of significant differences between land types and ROS is that they may often contain similar vegetation.

The ROS analysis among various land cover types yielded peat bog vegetation as the fastest spreaders and the coniferous and mixed forests as among the slowest (Fig. 5). It is likely a surprise that peat bogs are found to be the fastest spreading because of their attribution to smoldering creeping fire behavior. Yet among peatlands, fire spread is dominated by flaming combustion of surface fuels like grasses and shrubs (Santoso et al., 2019). The ROS being observed on this land cover are due to the surface fires spreading via the vegetation on the top layer and can include a number of mosses, herbaceous plants such as *Molinia*, woody plants, and dwarf shrubs (CLC). The aforementioned vegetation is not unique to peatlands and can also be found within the heathland and moorland land covers. The Forestry Commission ((2019b)) reported that while mountain, heath, and bogs only accounted for 1% of wildfires in the UK these fires were responsible for between 4 and 82% of the total burn area and include some of the more high profile fires in recent years, such as the ~1,000 ha Saddleworth Moor fire (2018) and the ~16,000 ha Knockando fire (2019). Gazzard et al. (Gazzard et al., 2016) performed an analysis of wildfire incidents from the

Incident Recording System data in the UK and identified that these mountain, moorland, and bog fires account for 40% of the area burnt in the region due to horizontal continuity of fuel, topography, and difficulty of suppression, which permits fires to spread. Open habitats, or landscapes not enclosed by trees, such as heathlands, typically permit greater surface wind speeds in the absence of obstacles and allow for uninterrupted fire spread (Linn and Cunningham, 2005). Within the Corine Land Cover classification map, most of the fire incidents on peat bogs within our study are located on more mountainous terrain in the Scottish highlands, which contain Flow Country, home to the largest peat bog in Europe, and the west coast of Ireland. There may be several potential reasons for the higher ROS within these areas, including possible synergies between topography and strong Atlantic winds, remoteness contributing to difficulty in accessibility or water availability limiting suppression, or greater horizontal fuel continuity from peat to surface vegetation and further research is required to explore these linkages.
Zooming in on the land cover type where rate of spread was slowest, mixed and coniferous forests exhibited among the slowest spread rates observed at 0.077 and 0.12 km/hr, respectively (Fig. 5). Between 2009–2017, woodland and forest fires accounted for less than 5% of the total burned area in the UK (Forestry Commission England, 2019). A plausible explanation for the slow ROS in these forests is that fires in these systems are wind-limited due to a more closed canopy; therefore, they may tend to be slower moving (Cochrane, 2003).

Overall, the ROS values were low to moderate. The fastest spreading fuel type, peat bog vegetation, only recorded a mean ROS of approximately 0.22 km/hr, which is not considered to be a fast moving fire. The reason for such low values may lie within the methodology implemented, which produced average spread rates. The ROS vectors were derived from the VIIRS satellite which has an overpass time of 12 hours. Developing the ROS vector over such a long time frame is likely to underestimate the actual ROS: it is unlikely that the fire progressed at a constant rate over the course of the timestep, especially as we are averaging the ROS over periods of night and day. Therefore there is a degree of variation that should be taken when relying on these estimations from VIIRS. This may also be the reason why there appears to be less variation among the different land cover types.

4.4 Implications for Fire Management

Accurate data on ROS among the represented land cover types as well as periods of peak activity are essential for determining periods of elevated fire risk, the effectiveness of available suppression techniques as well as appropriate mitigation strategies (land and fuel management). While this knowledge is abundantly available for regions that are familiar with wildfires, emerging fire prone regions often lack research in part due to limited records and past fire exposure. Northwest European forest and fire managers may use these results to inform people that they should be wary or prepared for incidents of wildfire in the months of April and May or even later in summer in years of severe drought (Fig. 3 & 4). These managers and fire suppression experts may also consider that the values for ROS are likely to be underestimated due to the methods implemented, particularly the averaging of ROS over 12 hour periods.

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Knowledge of the underlying conditions permitting fire spread will be essential for determining appropriate suppression methods. Furthermore there is a need to account for the prevalent smaller fires that are not captured by VIIRS. Even fires of smaller magnitude have the potential for widespread impact due to a higher urban density throughout northwest Europe. Estimates for ROS of these smaller fires may require a more ground-based approach until there is development towards a monitoring system of satellite sensors with higher spatial and temporal resolution such as that of the Canadian WildFireSat suitable for real time emergency management (Johnston et al., 2020). Higher resolution information pertaining to fuels will be necessary for identifying at risk vegetation types as well as for capturing fuel heterogeneity permitting fire spread. If increases in fire activity within this northwest European region are to be expected, it will be crucial to not only prepare for the fires experienced now, but ones of more adverse behavior. Steps towards characterizing the current and future fire behavior in this region should be further addressed to ensure future risks can be properly approached and mitigated.

5. Conclusions

The findings obtained in this study provide among the first estimations of wildfire rate of spread for northwest Europe and present a novel methodology towards the characterization of fire behavior in this newly fire prone region through the use of satellite hotspot detection. This technique identified 254 fires and has proven to be a useful alternative in the absence of infield measurements and years of data collection.
Regarding the seasonality of fires within northwest Europe, the months of April and May were identified as periods of peak fire activity in terms of heightened ROS and burned area. During this peak, 67% of the burned area occurs and median fire runs are approximately 0.16 km/hr during a 12 hour overpass. Surprisingly, there was no significant effect of land cover on ROS although, among the represented land covers, peat bog vegetation had the highest mean ROS of 0.21 km/hr, while mixed forests and pastures had the lowest of 0.077 km/hr and 0.1 km/hr respectively.
Steps towards characterizing the fire behavior in this region should be further addressed to ensure future risks can be properly approached and mitigated. Future analyses to characterize fire behavior and fire regime in northwest Europe should consider the fire frequency, duration, as well as the meteorological conditions contributing to ignitions.

Data availability. The data collected and produced is available on the Zenodo platform. The DOI and link of access is https://doi.org/10.5281/zenodo.6330201

Author Contributions. M.T. and A.C. conceived the idea; S.M. developed the algorithm and ran the analyses; M.T. and A.C. ran subsequent analyses and interpretation; M.T. led the writing of the manuscript. All authors contributed critically to writing and editing the drafts and gave the final approval for publication.

Competing Interests. The contact author has declared that neither they nor their co-authors have any competing interests.

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