

1 **Rapid satellite assessment of the 2026 High Fens fire**

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1 Rapid satellite assessment of the 2026 High Fens fire

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9 Abstract

10 Climate change is altering fire regimes across Europe, contributing to longer periods of
11 favorable fire weather. In August 2026, the High Fens nature reserve experienced one of
12 Belgium's largest recorded wildfires. This event is ecologically significant as it affected carbon-
13 dense peatlands vulnerable to smouldering combustion and carbon (C) release. This study
14 provides a satellite-based assessment of the fire and uses its pre-fire hydro-climatic conditions to
15 benchmark similar meteorological exposure across the High Northern Latitudes (HNL).
16 Sentinel-2 imagery delineated a 25.43 km² burn scar with heterogeneous spectral severity. VIIRS
17 data further showed the High Fens event was the largest peatland-dominated active fire cluster in
18 Western Europe during 2012–2026. To contextualize ignition preconditions, we used a
19 sequential feature selection algorithm over the 7 days prior to ignition to select maximum vapor
20 pressure deficit, daily evapotranspiration, and surface soil moisture to represent distinct,
21 relatively weakly correlated aspects of the extreme pre-fire environment. Upscaling this empirical
22 benchmark across the HNL revealed comparable extreme conditions concentrated along
23 southern margins of the high-latitude domain. Intersecting this exceedance footprint with global
24 peatland and MODIS MCD64A1 fire-history data identified 319,076 km² of peatland with no
25 MCD64A1-detected burned area during 2001–2025 containing 45.1 Gt C of soil organic carbon,
26 alongside 104,183 km² of previously burned peatland (12.6 Gt C). Translating this widespread
27 meteorological exposure into emission estimates requires precise understanding of belowground
28 fire behavior. The High Fens reserve's accessibility and existing pre-fire data offer a unique
29 opportunity for field-based validation of peat combustion and recovery.

31 Keywords: wildfire, Belgium, remote sensing, climate change, peatland

33 1. Introduction

34 Wildfire risk is increasing across Europe as climate change drives hotter, drier fire weather,
35 more frequent heatwaves, and more severe drought conditions, although realized burned area
36 also depends on fuels, ignitions, and fire management (Giannaros and Papavasileiou 2023;
37 Grünig et al. 2023; Jones et al. 2024; Santos et al. 2024). Extreme fire weather is expanding
38 beyond the Mediterranean into central, temperate, and some boreal regions, while fire seasons
39 are projected to lengthen across much of Europe, including northern areas (Carnicer et al. 2022;
40 El Garroussi et al. 2024; Hetzer et al. 2024). Model projections indicate that burned area is likely
41 to increase substantially, with Mediterranean Europe projected to see roughly 40% to
42 100% more summer burned area as warming rises from 1.5 to 3°C, and with temperate forests

becoming increasingly susceptible to damage under emerging fire regimes (Patacca et al. 2026; Turco et al. 2018). Regions that have historically experienced fewer large wildfires may therefore increasingly encounter periods of extreme fire weather in coming decades (Calheiros et al. 2021; El Garroussi et al. 2024; Miller et al. 2025). Against this backdrop, a major wildfire ignited in eastern Belgium's High Fens (Hautes Fagnes) nature reserve on August 14, 2026. The fire spread rapidly across the reserve, eventually becoming one of the largest wildfires in Belgium's recorded history and requiring a massive emergency response involving more than 250 personnel, aerial support, and the activation of the Copernicus Emergency Management Service (Associated Press 2026; DW News 2026; EU Space 2026; Reuters 2026; The Brussels Times 2026).

Crucially, this fire occurred in a peatland-dominated landscape (Henrion et al. 2024). Peatlands occupy a small fraction of Earth's surface yet store approximately one-third of global soil carbon (Dargie et al. 2017; Wilkinson et al. 2023). Drought exposes deeper peat to smouldering fires that consume millennia of accumulated carbon and alter hydrology (Kettridge et al. 2015; Rein and Huang 2021; Turunen et al. 2025). However, quantifying these losses remains difficult because remote sensing, particularly optical remote sensing, usually captures surface spectral change rather than actual burn depth or subterranean consumption (Ballhorn et al. 2009; Konecny et al. 2016; Nelson et al. 2026). The scarcity of spatially explicit observations limits the validation of belowground combustion and contributes to large uncertainty in regional emission estimates (van der Werf et al. 2010).

The 2026 High Fens Fire provides a rare opportunity to evaluate an unusually large temperate peatland fire and assess northern peat carbon exposure to similar pre-conditions. This study aims to: (1) quantify the event's spatial footprint using Sentinel-2; (2) contextualize the fire historically using VIIRS active-fire detections; and (3) utilize a feature selection algorithm to identify the most extreme, weakly correlated hydro-climatic anomalies to construct an empirical exposure index. By mapping this index across the High Northern Latitudes (HNL) and intersecting it with global peatland and burned-area datasets, we quantify soil organic carbon stocks in unburned northern ecosystems in recent decades exposed to comparable extreme weather.

2. Study area

The High Fens nature reserve (Figure 1) is a protected area of about 40 km² in eastern Belgium, on the Stavelot-Venn Massif within the Ardennes region near the German border (Goemaere et al. 2016). The region has a humid and cold climate and a pronounced topographic gradient (Mormal and Tricot 2004), and its highest point reaches 694 m above sea level, which represents the highest elevation in the country (Henrion et al. 2024; Keulen et al. 2005).

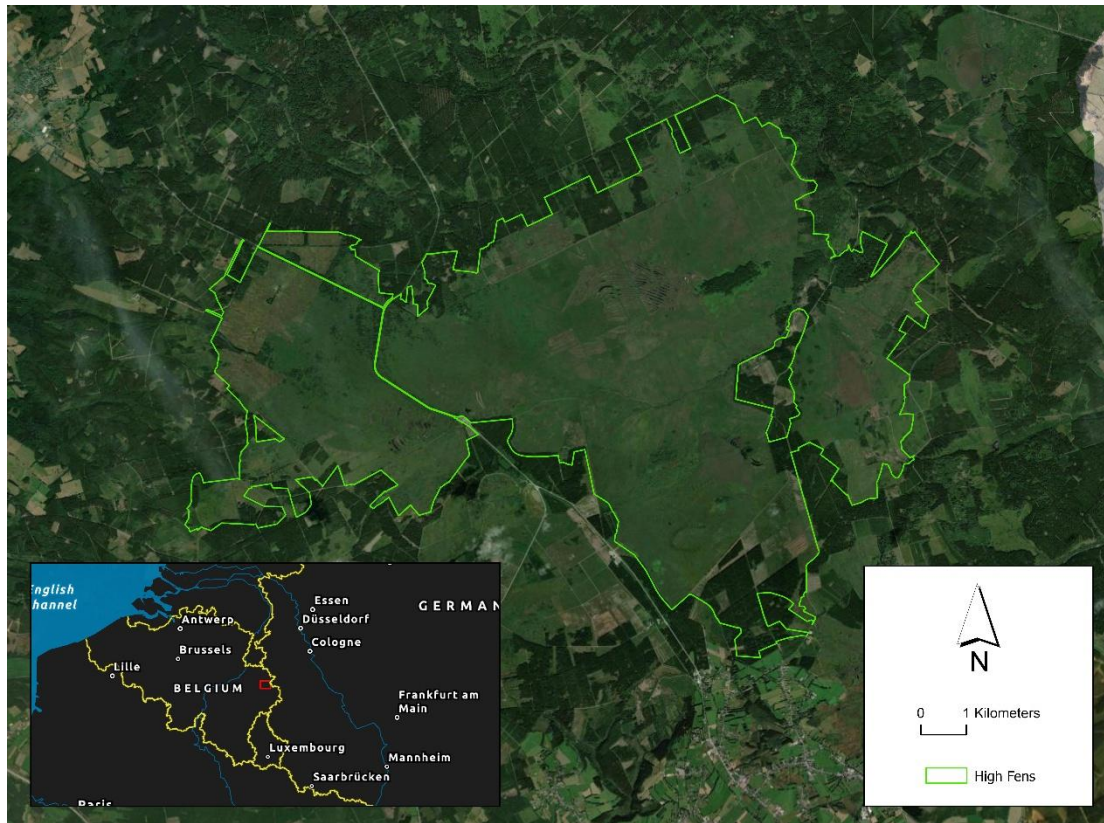


Figure 1. The study area. The boundary of the High Fens Nature Reserve is adopted from the World Database on Protected and Conserved Areas dataset (UNEP-WCMC and IUCN 2026). The location of the study area relative to Belgium and surrounding regions is indicated by the red box in the inset.

The reserve is dominated by peatland ecosystems, especially raised bogs, alongside wet moors linked to peat-bog degradation (Keulen et al. 2003; Li et al. 2024). These environments support vegetation adapted to acidic, waterlogged conditions, including peat-forming Sphagnum mosses, dwarf shrubs, and graminoids such as *Molinia caerulea* (Hindryckx 1999; Keulen et al. 2003). Created in 1957 to protect peatlands from further degradation, the High Fens is one of Belgium's most important peat-bog landscapes and a significant site for ecological and peatland research (Goemaere et al. 2016).

To place the High Fens Fire in a broader regional context, we defined the Western European analysis domain using the United Nations Geospatial Database (<https://www.un.org/geospatial/>) regional classification. This domain was used only for the historical VIIRS fire-cluster comparison. For the circumpolar analysis, we defined the HNL as all land areas north of 50°N.

3. Methodology

3.1. Sentinel-2 burn scar mapping and dNBR assessment

To estimate the spatial extent of the High Fens Fire, we mapped its burn scar at a 20 m spatial resolution using paired Sentinel-2 Level-2A surface reflectance images. We selected the closest sufficiently cloud-free pre-fire (July 25, 2026) and post-fire (August 26, 2026) observations available relative to the August 14 ignition date. Using these images, we calculated

the differenced Normalized Burn Ratio (dNBR). Burned and unburned reference polygons were manually identified from the post-fire imagery. We evaluated candidate dNBR thresholds using receiver operating characteristic analysis to identify the threshold providing the maximum separation between the reference samples (see Section S1 for explicit formulations and threshold optimization details). The resulting threshold was then applied to the full dNBR image to delineate the mapped burn scar.

3.2. VIIRS fire-cluster footprint calculation for historical wildfire context in Western Europe

The High Fens Fire was unusually large for Belgium, but its regional significance is best evaluated by comparing its footprint with other events. We derived fire-associated footprints from Suomi-NPP VIIRS 375 m active-fire detections for 2012 to 2026. To distinguish wildfires from persistent thermal anomalies, candidate links were identified between detections occurring within 750 m and 14 days of one another. Spatially expanding fires were grouped into discrete multi-day events using a spatiotemporal clustering algorithm (detailed in Section S2). To filter prolonged point-source anomalies while retaining expanding fires, detections occurring more than seven days after a cell's initial detection were excluded. Retained clusters required a minimum of three detections. Finally, each detection was represented by a 375 m by 375 m cell, and overlapping cells within each cluster were dissolved to estimate a single areal footprint. To evaluate the High Fens wildfire within a broader regional context, we applied this active fire clustering method across Western Europe. We compared the High Fens cluster against all other clusters by total area and land cover composition. Land cover was derived from the static 100 m European Environment Agency Coordination of Information on the Environment (CORINE) dataset for 2018 (see Section S3 for the reclassification scheme).

3.3. Pre-fire hydro-climatic conditions and High Fens Fire Index construction

To characterize pre-fire hydro-climatic conditions, we evaluated seven candidate daily summer variables (June–August (JJA), 2016–2026) extracted from ERA5-Land and the NASA Soil Moisture Active Passive (SMAP) Level-4 product: maximum air temperature, accumulated precipitation, mean wind speed, surface solar radiation, daily evapotranspiration (ET), maximum vapor pressure deficit (VPD_{max}), and surface soil moisture (SSM). VPD_{max} was calculated as the difference between saturation and actual vapor pressures (Allen et al. 1998), derived from ERA5-Land 2m temperature and dewpoint temperature.

We applied a sequential feature selection algorithm over the 7 days preceding ignition (August 7–13, 2026) to identify the most anomalous pre-fire conditions while limiting redundancy among variables. This approach selected a subset of three variables by maximizing their pre-fire anomaly magnitude while minimizing their pairwise collinearity. Variables were ranked based on their absolute standardized anomaly during the pre-fire week compared to their 10-year baseline. The algorithm selected the most anomalous variable first, then sequentially selected two subsequent variables that exhibited severe anomalies but penalized them based on their average absolute Pearson correlation with the already-selected variables. The correlation penalty weight was set to 1.0, and correlations were calculated across the entire June 1–August 13 summer period to ensure a robust sample size.

To quantitatively characterize these conditions, daily summer values for the three selected

variables were standardized into standard anomalies against their 10-year baseline statistics (2016–2025). Where necessary, anomalies were sign-reversed so that positive values consistently represented conditions associated with drying and increased fire favorability. To assess environmental similarity to the pre-fire benchmark on any given summer day, the scalar High Fens Fire Index (HFFI) was computed as the projection of the daily standardized anomaly vector onto the exact August 13 benchmark vector (see Section S4 for the mathematical formulation). Daily HFFI trajectories and multi-year summer matrices were constructed to identify periods during which conditions reached or exceeded the benchmark ($\text{HFFI} \geq 1.0$).

3.4. High Northern Latitude upscaling of HFFI

To assess the geographic extent of areas experiencing comparable pre-fire conditions, the HFFI framework was expanded circumpolarly. Daily summer grids of VPD_{max} , ET, and SSM for 2016–2026 were extracted for landmasses north of 50°N using Google Earth Engine, resampled to a 50 km resolution to overcome memory limitations. These hemispheric rasters were standardized using the 2016–2025 baseline statistics (μ and σ) calculated at the High Fens Nature Reserve centroid. Consequently, HFFI values represent similarity to the High Fens pre-fire anomalies rather than local climate extremes at each HNL pixel.

We summarized the daily HFFI time series into annual exceedance-count rasters, indicating the cumulative number of days per year where conditions met or exceeded the benchmark ($\text{HFFI} \geq 1.0$). To quantify peatland area and soil organic carbon stocks within this footprint, we integrated 1-km PEATGRIDS Global Peat Thickness and Carbon Stock data (Widyastuti et al. 2025) with MCD64A1 Collection 6.1 burned-area data (Giglio et al. 2018). We generated a cumulative mask from MCD64A1 to classify peatland pixels as burned (fire detected during 2001–2025) or unburned (no detected fire). These categories were intersected with the $\text{HFFI} \geq 1.0$ footprint. Total soil organic carbon stock for each category was calculated by summing the PEATGRIDS carbon-stock values across all included pixels. Because pixel-level errors in global soil models are highly spatially autocorrelated, aggregating them assuming statistical independence underestimates regional uncertainty. We therefore report aggregated mean carbon stocks as best estimates without propagated pixel-level variance, noting that actual uncertainties scale with the baseline PEATGRIDS dataset.

4. Results

4.1. Spatial extent and surface spectral change of the High Fens Fire

The Sentinel-2 imagery captured pronounced surface changes between the July 25 pre-fire and August 26 post-fire observations (Figure 2). Applying a dNBR threshold of 0.192 (which was determined based on the receiver operating characteristic analysis), we mapped a 25.43 km² (2,543 ha) burn scar across the central and eastern portions of the reserve. Within this footprint, dNBR values exhibit considerable spatial heterogeneity, indicating substantial variation in the magnitude of surface spectral change across the burned landscape.

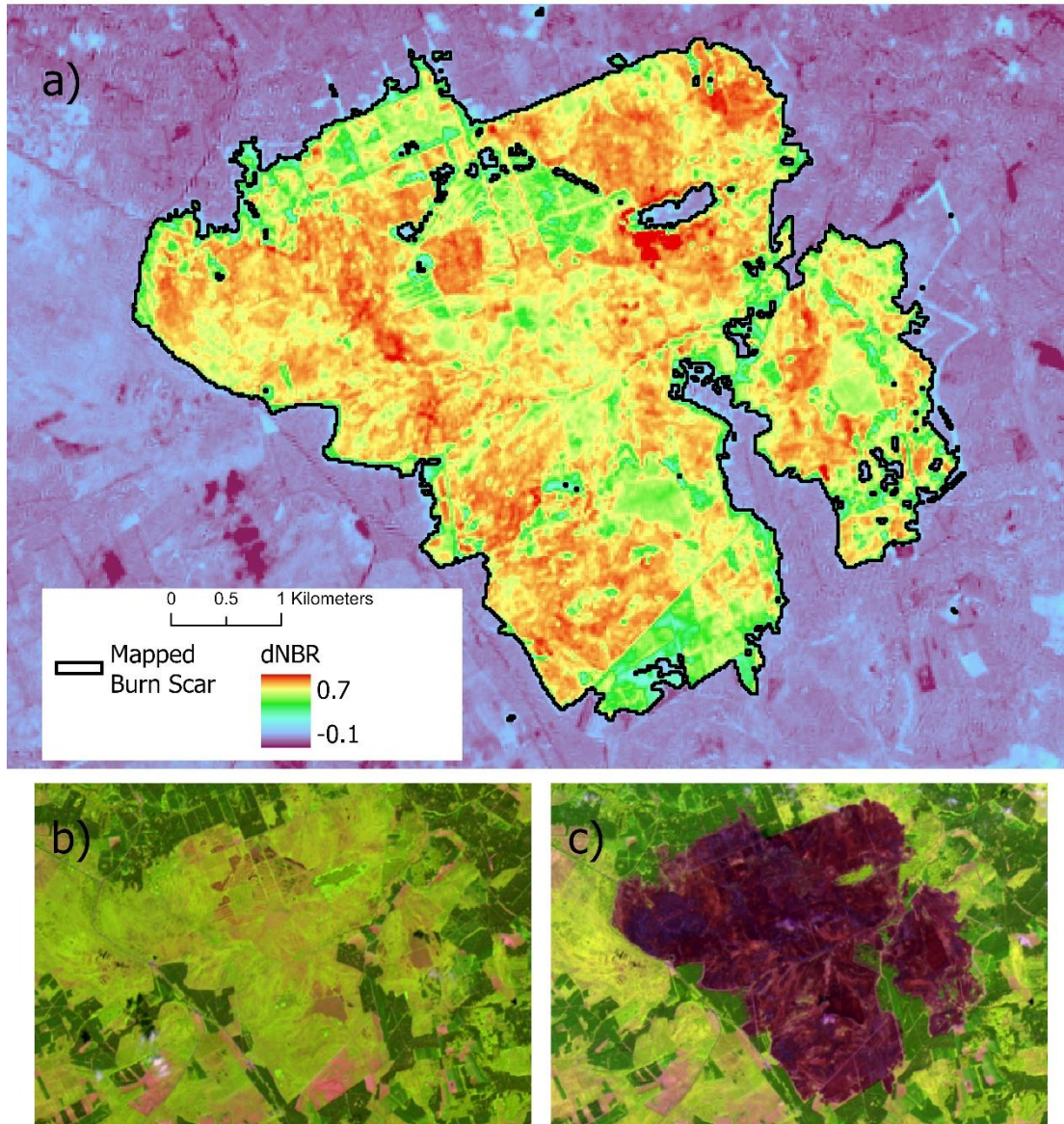


Figure 2. Spatial extent and spectral severity of the 2026 High Fens Fire. (a) Differenced Normalized Burn Ratio (dNBR) derived from Sentinel-2 imagery, with the mapped burn scar outlined in black. The color scale represents dNBR values, with higher positive values indicating greater spectral change between the pre- and post-fire observations. (b) Pre-fire Sentinel-2 image acquired on July 25, 2026. (c) Post-fire Sentinel-2 image acquired on August 26, 2026.

4.2. Regional context of the High Fens Fire

The VIIRS active-fire clustering identified the High Fens Fire as a 35.20 km² fire-associated footprint, compared with a 25.43 km² burn scar mapped from Sentinel-2 imagery. The two estimates show broadly similar spatial patterns, but the VIIRS-derived footprint extends beyond the Sentinel-2 mapped scar, particularly along the western side of the fire-affected area (Figure 3). This discrepancy may be attributed to artifacts common in moderate-resolution active fire datasets, as the coarse 375 m pixel size or the downwind drift of hot smoke plumes could potentially trigger thermal anomalies outside the actual surface combustion boundary (Pinto et al. 2024).

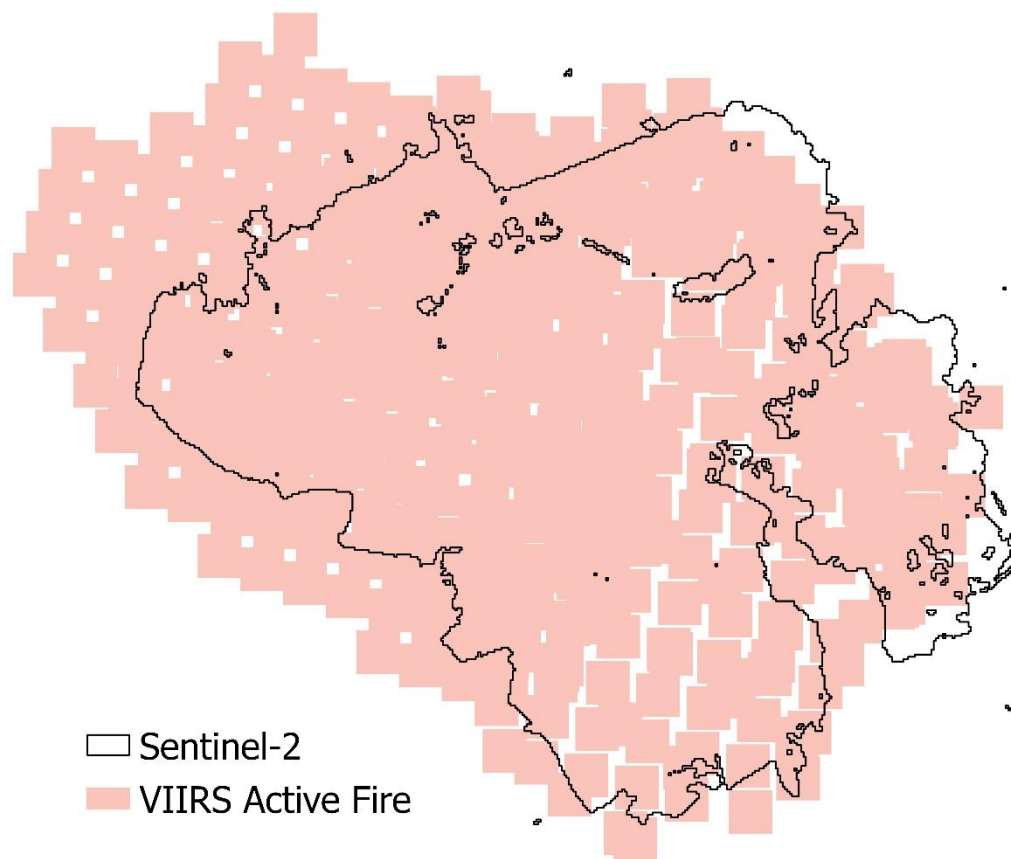


Figure 3. Spatial extent of the 2026 High Fens Fire derived from Suomi-NPP VIIRS active fire detections and comparison with the Sentinel-2 mapped burn scar. The pink area represents the VIIRS active-fire-derived fire footprint, while the black outline represents the Sentinel-2 mapped burn scar. The VIIRS-derived footprint extends beyond the Sentinel-2 mapped scar, particularly along its western side.

In the broader Western European fire-cluster perspective, the High Fens Fire ranked sixth among the VIIRS-derived fire clusters identified by our method across the Western European domain during 2012–2026 (Table 1). The five larger clusters were all located in France, with areas ranging from 39.41 to 172.17 km². The High Fens Fire was therefore the largest VIIRS fire cluster identified in Belgium during the analysis period and ranked among the largest events identified across the broader Western European domain.

The land cover composition of the High Fens Fire event differed markedly from that of the five larger regional clusters (Table 1). Within the High Fens VIIRS-derived event footprint, 63% of the area was classified by CORINE Land Cover 2018 as peat bog, 36% as forest, and 1% as grassland. In contrast, the five larger clusters were dominated by forest, which accounted for 81–96% of their respective footprints. The High Fens event was therefore the only active fire cluster among the six largest regional active fire clusters between 2012 and 2026 in which peatland constituted the majority of the VIIRS-derived fire-associated footprint.

Table 1. The six largest VIIRS active fire clusters identified across Western Europe during 2012–

2026, ranked by cluster area. For each fire cluster, the table reports the centroid location, country, year, start and end dates, area, and land cover composition.

Rank by Size	Centroid Latitude	Centroid Longitude	Country	Year	Start Date	End Date	Area (km ²)	Land Cover Composition
1	44.86190	-1.081320	France	2026	07-20	07-27	172.17	Forest (95%), Urban (3%), Cropland (1%), Others (1%)
2	44.52230	-0.527275	France	2022	07-13	07-20	121.80	Forest (96%), Cropland (2%), Urban (1%), Others (1%)
3	44.48970	-0.734756	France	2022	08-11	08-13	41.23	Forest (93%), Cropland (4%), Urban (3%)
4	44.75310	-0.896140	France	2026	07-25	07-29	40.82	Forest (92%), Cropland (4%), Urban (4%)
5	44.40250	-1.124730	France	2026	07-23	07-29	39.41	Forest (81%), Urban (14%), Cropland (3%), Water (1%), Wetland (1%)
6	50.52700	6.093840	Belgium	2026	08-14	08-17	35.20	Peatland (63%), Forest (36%), Grassland (1%)

4.3. Pre-fire hydro-climatic anomalies and HFFI trajectories

Our sequential feature selection algorithm ultimately selected VPD_{max} , ET, and SSM as the three variables combining large pre-fire anomalies with comparatively low mutual correlation. To characterize pre-fire environmental conditions from June 1 to August 13, 2026, we monitored these three variables against their 10-year summer baselines (Figure 4). VPD_{max} exceeded its historical mean (1.1 kPa) in mid-June and remained mostly elevated, peaking at 4.0 kPa on August 13, the eve of the fire. SSM was initially well above the historical average but steadily declined after mid-June, dropping sharply back to seasonal minimums immediately preceding the fire. Notably, ET fell below its summer mean from mid-July (minimum ≈ 1.7 mm on $\sim$ July 23) and remained below average through ignition (≈ 2.7 – 3.1 mm during August 7–13), while VPD_{max} reached its seasonal maximum. Ultimately, the daily trajectories of VPD_{max} , ET, and SSM captured the severe atmospheric demand and substrate drying characterizing the pre-fire buildup.

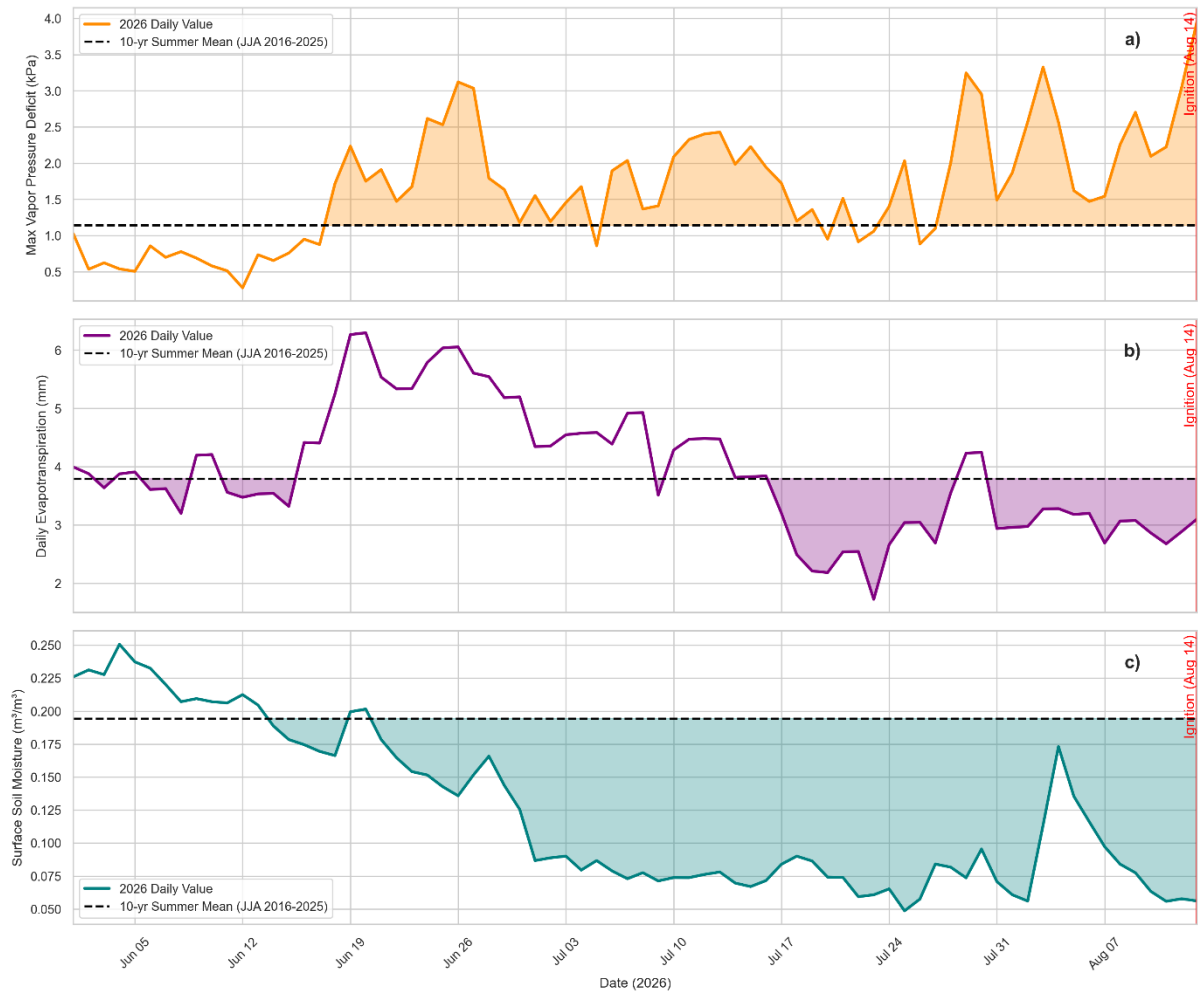


Figure 4. Pre-fire hydro-climatic trajectories at the High Fens Nature Reserve centroid during the summer of 2026. Panels display (a) daily maximum vapor pressure deficit (VPD_{max} , kPa), (b) daily evapotranspiration (ET, mm), and (c) surface soil moisture (SSM, m^3/m^3). The red vertical line indicates the wildfire ignition date (August 14, 2026), and black dashed horizontal lines represent the 10-year historical summer mean (JJA 2016–2025). Shaded regions denote daily departures from the long-term baseline.

The HFFI summarizes the combined hydro-climatic anomalies by projecting daily states onto the August 13 benchmark vector, where $HFFI \geq 1.0$ represents conditions meeting or exceeding this pre-fire state (Figure 5). The HFFI benchmark was not reached at the site during the 2016–2025 baseline period. The index approached 1.0 most closely during the historic European heatwave of July 24–26, 2019, but ultimately fell short, highlighting the exceptional severity of the 2026 pre-fire environment. It is worth noting that VIIRS recorded no active fires in the reserve between 2012 and the August 2026 ignition (results not shown).

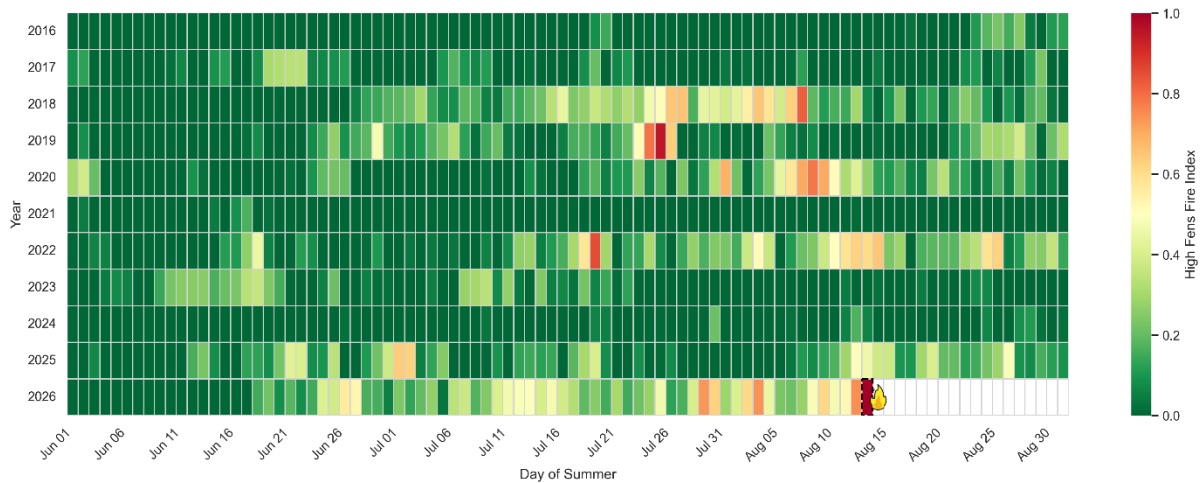


Figure 5. Summer daily heatmap of similarity to the pre-fire benchmark for the High Fens Fire Index (HFFI) from 2016 to 2026. Daily HFFI values are shown from lower to higher similarity to the High Fens pre-fire benchmark. Black dashed boxes outline days meeting or exceeding the HFFI benchmark threshold of 1.0, and the flame icon marks the August 14, 2026, fire ignition date.

4.4. Circumpolar HFFI upscaling and peatland fire-history overlap

To evaluate the geographic distribution of hydro-climatic conditions comparable to those preceding the High Fens Fire, the HFFI was upscaled to all HNL spanning the summer months of 2016 to 2026 (Figure 6). This hemispheric projection mapping reveals that the hydro-climatic conditions recorded immediately prior to the High Fens Fire are not uniform across the HNL, but are geographically restricted. Regions experiencing at least one day meeting or exceeding the HFFI benchmark threshold ($\text{HFFI} \geq 1.0$) occupy a distinct latitudinal belt concentrated along the southern margins of the high-latitude domain (highlighted in pink in Figure 6). HFFI exceedances were concentrated primarily across southern Canada, western, central, and eastern Europe, and the southern transition zones of Siberia. In contrast, the vast majority of the high-latitude domain, including Alaska, northern and central Canada, Scandinavia, and northern Siberia, did not experience a single day of critical exceedance (represented in blue, denoting 0 days, in Figure 6).

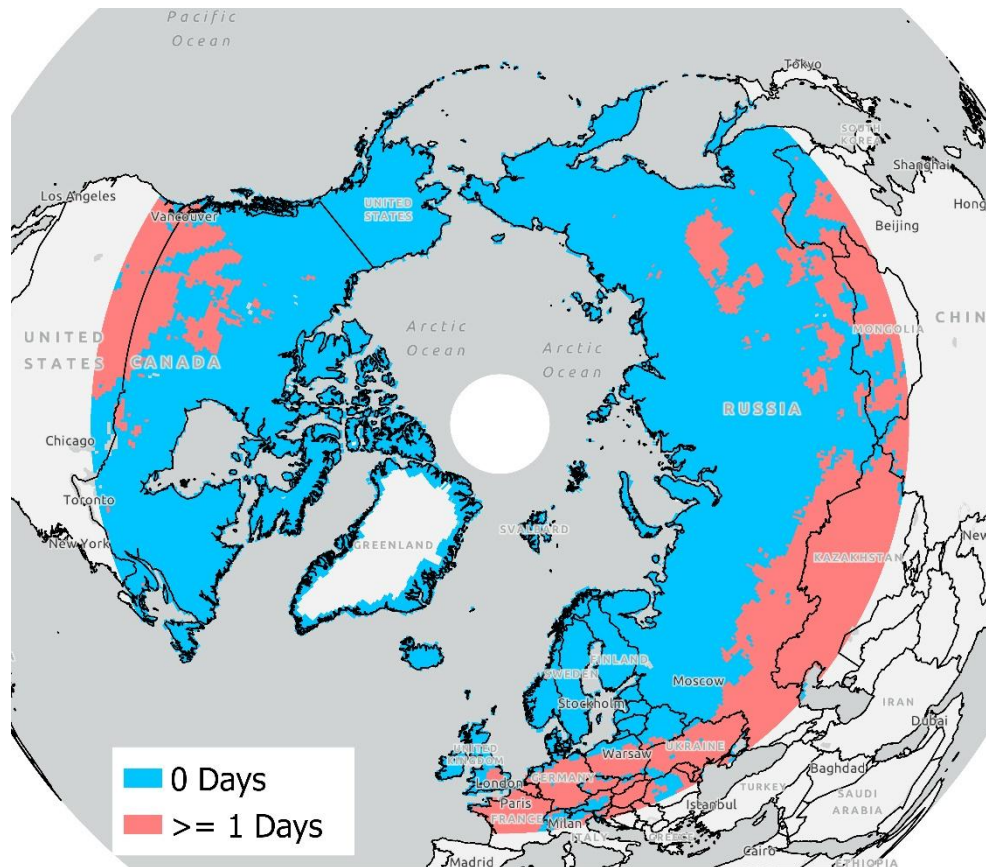


Figure 6. Circumpolar HNL mapping of the High Fens Fire Index (HFFI) exceedance footprint over the summer seasons (JJA 2016–2026). Blue regions denote areas with zero exceedance days, while pink shaded regions isolate geographic areas that met or exceeded the HFFI benchmark threshold of vapor pressure deficit, evapotranspiration, and surface soil moisture ($HFFI \geq 1.0$) on at least one daily interval.

Integrating this HFFI exceedance pattern with circumpolar peatland distributions and the 2001–2025 MCD64A1 burned-area record reveals substantial peat carbon stocks occurring within areas that experienced comparable hydro-climatic conditions. Overlapping the PEATGRIDS-derived 1 km peatland map with the 25-year MCD64A1 dataset shows a detailed spatial distribution of burned and unburned peatland areas that fall directly within this HFFI exceedance footprint (Figure 7). Because the extreme fire weather footprint is restricted to the southern margin of the domain, the resulting HFFI-exposed peatland areas are selectively situated along these transitional zones, rather than across the vast northern peatland. Importantly, this spatial overlay highlights that while historically burned peatlands (represented in red) mark localized zones of active disturbance, they are outweighed by vast, contiguous networks of unburned peatlands (represented in cyan) that are directly exposed to these extreme climate anomalies (Figure 7). These peatlands that are unburned in recent decades (according to the MCD64A1 product) contain substantial carbon stocks located in areas where comparable severe hydro-climatic conditions occurred.

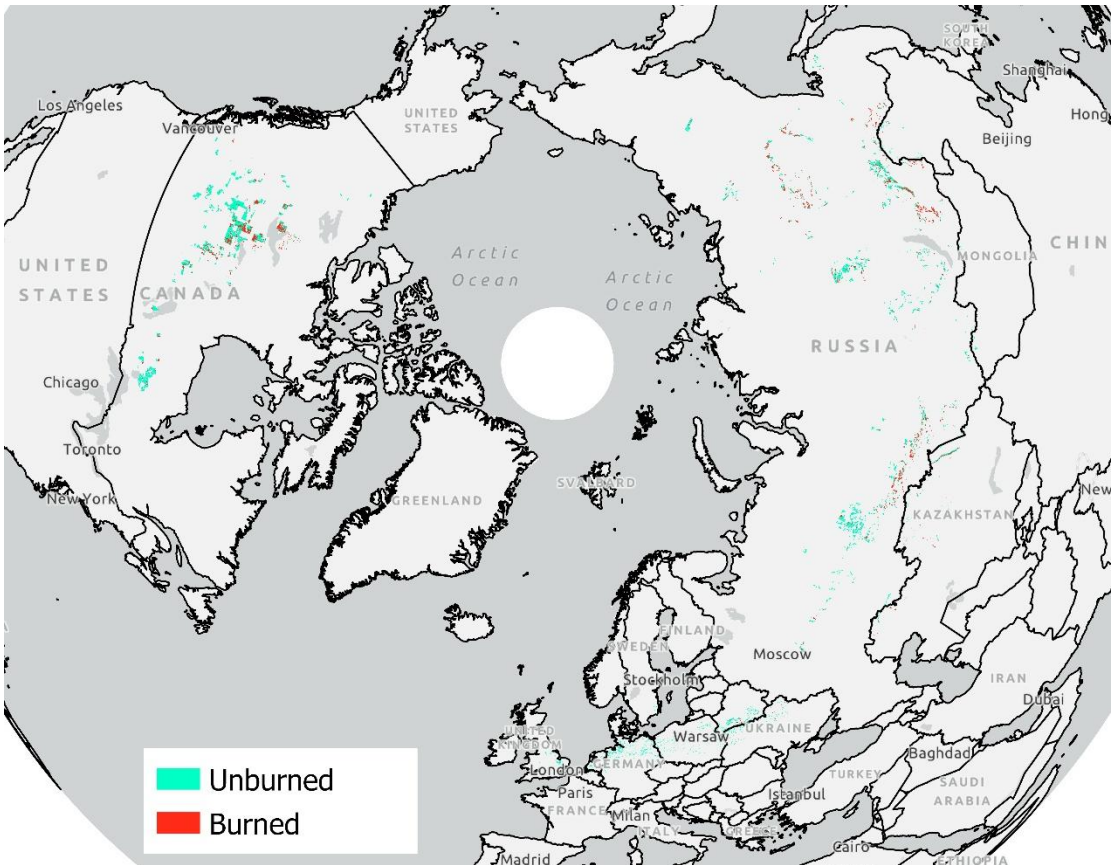


Figure 7. Spatial overlay of circumpolar peatland ecosystems intersecting the HFFI exceedance footprint. HFFI-exposed peatland areas are categorized into unburned peatlands (cyan) and peatlands with MCD64A1-detected burned area during 2001–2025 (red).

The total area and absolute soil organic carbon pools for these circumpolar peatland scenarios are quantitatively summarized in Table 2. Across the HNL domain, peatlands without MCD64A1-detected burned area during 2001–2025 covered 6,051,266 km² and contained an estimated 802.9 Gt C of soil organic carbon. Peatlands with MCD64A1-detected burned area covered 570,240 km² and contained 75.9 Gt C. Within the HFFI exceedance footprint, 319,076 km² of peatland had no detected burned area during 2001–2025 and contained 45.1 Gt C, whereas 104,183 km² had detected burned area and contained 12.6 Gt C. Across the HNL peatland domain, 8.6% of the mapped peatland area had MCD64A1-detected burned area during 2001–2025. Within the HFFI exceedance footprint, 24.6% of the mapped peatland area had detected burned area.

Table 2. Quantitative summary of peatland area and soil organic carbon stocks across the HNL and within the HFFI exceedance footprint. Burned and unburned categories are based on MCD64A1-detected burned area during 2001–2025.

Scenario Category	Area (km ²)	Total Soil Carbon (Gt C)
Total HNL Land, Unburned	6,051,266	802.9
Total HNL Land, Burned	570,240	75.9

HFFI Exposed, Unburned	319,076	45.1
HFFI Exposed, Burned	104,183	12.6

5. Discussion

5.1. The High Fens Fire and opportunities for monitoring peatland recovery

The significance of the 2026 High Fens Fire extends beyond its mapped extent. Sentinel-2 imagery identified a 25.43 km² burn scar exhibiting substantial spatial heterogeneity in dNBR, indicating a highly variable surface response across the reserve. However, while the fire occurred primarily within a peat-covered landscape, satellite surface reflectance cannot partition combustion between aboveground vegetation and the underlying organic soil. High dNBR values reflect severe canopy consumption, vegetation scorch, and surface charring, but they do not provide direct evidence of the depth or mass of peat consumed below the surface. Unlike predominantly aboveground forest fires, peatland fires can involve prolonged subterranean smouldering that triggers massive carbon loss and severe ecological shifts.

The High Fens Fire provides an opportunity to examine peatland recovery following a large disturbance in a landscape where nearby pre-fire observations are available. Previous work by Li et al. (2024) characterized peat thickness and carbon storage at field sites approximately 2 km from the mapped burn scar, documenting substantial spatial variation in these properties over relatively short distances. The spatial variation in dNBR within the Sentinel-2 burn scar similarly indicates a heterogeneous surface response to fire, but the ecological and biogeochemical consequences of this variation cannot be determined from the initial post-fire observations alone. Crucially, if post-fire measurements are carried out soon, the combination of the reserve's accessibility and the adjacent pre-fire data could be greatly helpful in understanding peatland wildfire emissions. This presents a rare opportunity to link surface burn severity with long-term peatland recovery and carbon flux. Repeated observations of soil moisture, water-table conditions, vegetation composition, and surface elevation could help determine whether the High Fens Fire produces persistent changes in ecosystem structure or hydrological functioning.

5.2. A broader context for circumpolar peatland exposure

The High Fens pre-fire benchmark was unprecedented at the site during 2016 to 2026, with conditions only closely approaching the threshold during a three-day period in July 2019. When applied across the HNL, comparable conditions were concentrated primarily along the southern margins of the domain. This spatial pattern indicates that the hydro-climatic combination observed before the High Fens Fire has occurred elsewhere across northern peatland regions, but its occurrence alone does not imply fire susceptibility.

The peatland overlay demonstrates that 319,076 km² of northern peatlands unburned in recent decades have recently been exposed to comparable extreme fire weather. These intact areas contain an estimated 45.1 Gt C of soil organic carbon. The size of this unburned, yet meteorologically exposed, peatland carbon pool highlights a substantial latent risk. If extreme fire weather facilitates novel ignitions and subsequent deep smouldering in these ecosystems, the resulting carbon release could be substantial. However, carbon loss from peat combustion is highly sensitive to the depth of burning. The carbon stocks reported here provide an estimate of the amount of carbon present within peatlands exposed to the benchmark, rather than an estimate of future fire emissions, which will depend heavily on local burn depth and ignition

sources.

5.3. Interpretation and limitations of the HFFI framework

The HFFI should be interpreted as an empirical benchmark derived from the High Fens Fire, not a predictive fire-susceptibility model. It represents the combined maximum vapor pressure deficit, daily evapotranspiration, and surface soil moisture anomalies observed immediately pre-fire. Because reference statistics from High Fens were applied uniformly across the circumpolar domain, HFFI values indicate similarity to the High Fens pre-fire environment rather than local climatic extremes. Furthermore, the index threshold is event-derived and unvalidated independently. Even when conditions approach the benchmark locally (such as in July 2019) or exceed it across the hemisphere, extreme weather does not guarantee a wildfire without concurrent ignitions and favorable fuels. Other structural limitations include the event-specific variable selection algorithm, the additive equation allowing variable compensation, and the scale mismatch between a point-based baseline and 50 km hemispheric grids. Because the HFFI relies on an additive vector projection, extreme anomalies in one variable can compensate for less extreme conditions in another, meaning $\text{HFFI} \geq 1.0$ indicates aggregate severity rather than every variable individually exceeding its pre-fire benchmark.

The 50 km circumpolar analysis identifies broad regional patterns but cannot resolve fine-scale peatland heterogeneity. Additionally, the 1 km peatland dataset contains inherent uncertainties in delineation and carbon storage. The identified 319,076 km² of unburned peatland should therefore be interpreted as a regional-scale estimate of potentially exposed area rather than a precise delineation of fire susceptibility. Moreover, surface soil moisture at the 0 to 5 cm depth does not characterize deeper peat moisture or water-table position, which ultimately govern peatland fire combustion (Hokanson et al. 2016; Hokanson et al. 2018; Link et al. 2023). Similar caution is required for the fire-history layer, which was derived from MCD64A1 rather than the VIIRS footprints used regionally. Because moderate-resolution algorithms often omit peatland fires (Vetrita et al. 2021), our classification of peatlands with no detected fire history likely includes areas with undetected small, low-intensity, or subterranean burns. Finally, the reported carbon estimates represent existing soil organic carbon stocks within mapped areas, not potential emissions. Actual combusted carbon depends on ignition, fire behavior, and burn depth unquantified by the HFFI. Ultimately, the HFFI serves as a consistent empirical framework to contextualize the severe hydro-climatic conditions of a single unexpected wildfire within a broader circumpolar scale.

6. Conclusion

The 2026 High Fens Fire illustrates that extensive peatland fires can occur in temperate environments, outside the traditionally studied boreal, Arctic, and tropical regions. While multi-scale satellite remote sensing facilitates rapid response, with near-real-time VIIRS providing early detection and Sentinel-2 mapping spatial burn severity, the highly variable surface response emphasizes that optical sensors alone cannot directly infer combustion depth or associated carbon loss. To overcome these limitations, future observations incorporating active sensors, such as the recently launched NASA-ISRO Synthetic Aperture Radar (NISAR) and the upcoming European Space Agency (ESA) Radar Observing System for Europe in L-band (ROSE-L), will provide critical interferometric capabilities. These missions may provide spatially

extensive observations of post-fire surface deformation that, when combined with field measurements, could help constrain peat subsidence and combustion-related elevation change.

The severe pre-fire combination of high atmospheric moisture demand, suppressed evapotranspiration, and declining surface soil moisture also occurred across extensive areas of southern Canada, Europe, and southern Siberia. Crucially, these conditions intersected with vast unburned northern peatlands, highlighting a notable vulnerability in the northern carbon pool as extreme hydro-climatic anomalies occur. Because actual emissions heavily depend on local ignitions, fuel conditions, and hydrology, the HFFI serves as an empirical benchmark rather than a predictive emissions model. Ultimately, combining emerging satellite technologies with long-term field monitoring at this highly accessible site will yield foundational insights into how carbon-dense ecosystems respond to novel fire regimes under a warming climate.

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S1. Sentinel-2 Burn Scar Delineation and Threshold Optimization

We calculated the differenced Normalized Burn Ratio (dNBR) from the respective pre-fire and post-fire NBR values, following the formulas provided by Key and Benson (2006) and Delcourt et al. (2021):

$$NBR = \frac{Band\ 8A - Band\ 12}{Band\ 8A + Band\ 12}$$
$$dNBR = NBR_{pre} - NBR_{post}$$

We evaluated candidate dNBR thresholds using receiver operating characteristic (ROC) analysis, calculating the true-positive rate (TPR) and false-positive rate (FPR) across the range of observed dNBR values. Youden's J statistic ($J = TPR - FPR$) (Youden 1950) was used to identify the threshold providing the maximum separation between the reference burned and unburned samples. These manually identified polygons were utilized exclusively for threshold calibration to determine the optimal classification boundary, not as an independent accuracy assessment dataset.

S2. Spatiotemporal Clustering Algorithm for VIIRS Active Fire Detections

A k-d tree algorithm (Bentley 1975) was used to recursively partition the active fire detection data space, enabling the efficient identification of localized detection pairs without exhaustive comparisons among all observations. Because the k-d tree only identifies pairwise connections, a graph connected-components analysis (Hopcroft and Tarjan 1973) was subsequently applied. By treating individual fire detections as network nodes and their spatiotemporal proximity as connecting edges, this algorithm traced transitive connections to group spatially expanding fires into discrete multi-day events. These algorithms were implemented in Python using the `scipy.spatial` (Virtanen et al. 2020) and `networkx` (Hagberg et al. 2008) modules.

S3. CORINE Land Cover Reclassification Scheme

To resolve the high thematic detail of the 44 native CORINE Level 3 classes and minimize classification noise during regional wildfire comparisons, the land cover classes were reclassified and grouped into a simplified eight-class system: Forests, Grassland, Peatland, Wetland, Water, Cropland, Urban, and Others. Under this unified classification scheme, artificial and developed surfaces (CLC codes 111 to 142, representing continuous/discontinuous urban fabric, industrial sites, mines, and artificial vegetated areas) were aggregated as “Urban”. Agricultural lands (CLC codes 211 to 244, including arable land, pastures, and complex heterogeneous agricultural patterns) were consolidated as “Cropland”. Tree-covered areas (CLC codes 311 to 313, covering broad-leaved, coniferous, and mixed forests), along with transitional woodland-shrub communities (CLC code 324), were grouped under “Forests”. Natural grasslands (CLC code 321) and moors and heathlands (CLC code 322) were consolidated into the “Grassland” class to represent open herbaceous and shrubby fuels. Peat bogs (CLC code 412) were classified as “Peatland”, while other wet ecosystems, including inland marshes (CLC code 411) and coastal wetland systems (CLC codes 421 to 423), were grouped under a distinct “Wetland” class. Continental and marine water bodies (CLC codes 511 to 523) were consolidated under “Water”. Finally, structurally sparse, barren, or transient land covers (including sclerophyllous vegetation 323, bare rock, beaches, and burnt areas 331 to 335) were aggregated as “Others”.

S4. Mathematical Formulation of the High Fens Fire Index

Daily summer baseline statistics, including means (μ) and standard deviations (σ), for the three selected variables were computed over the 2016-2025 baseline period at the centroid

coordinates of the nature reserve. Daily summer values across the study period (2016-2026) were then standardized into standard anomalies (Z-scores):

$$Z_{VPD_{max}} = \frac{VPD_{max} - \mu_{VPD_{max}}}{\sigma_{VPD_{max}}}$$

$$Z_{ET} = (-1) \times \frac{ET - \mu_{ET}}{\sigma_{ET}}$$

$$Z_{SSM} = (-1) \times \frac{SSM - \mu_{SSM}}{\sigma_{SSM}}$$

The anomalies for evapotranspiration (Z_{ET}) and surface soil moisture (Z_{SSM}) were calculated as the negative of the standardized deviation to invert the scale, ensuring that positive anomalies uniformly represent desiccated, fire-favorable conditions (i.e., increased atmospheric demand, decreased evaporative flux, and decreased soil moisture). To assess environmental similarity to the pre-fire benchmark on any given summer day, the scalar High Fens Fire Index (HFFI) was computed as the projection of the daily anomaly vector onto the August 13 benchmark vector:

$$HFFI = \frac{Z_{VPD_{max}} \cdot Z_{VPD_{max},target} + Z_{ET} \cdot Z_{ET,target} + Z_{SSM} \cdot Z_{SSM,target}}{(Z_{VPD_{max},target})^2 + (Z_{ET,target})^2 + (Z_{SSM,target})^2}$$

where $Z_{VPD_{max},target}$, $Z_{ET,target}$, and $Z_{SSM,target}$ represent the standardized anomalies recorded on August 13, 2026.

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