Anomalous Moisture Signal in Sentinel-2 Imagery Precedes Overwintering Wildfire

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Abstract

Not all Canadian wildfires are extinguished by winter snowfall, instead smouldering underground for months before reemerging as flaming wildfires the following spring. Although these overwintering wildfires are difficult to manage and prevent, until recently this has been an uncommon phenomenon. This changed following the record-breaking 2023 wildfire season, when dozens of suspected overwintering wildfires reemerged in the spring of 2024, especially in the western boreal. In this study we identify overwintering wildfires through co-located thermal anomalies from late 2023 and early 2024. We investigate pre-fire multispectral Sentinel-2 imagery within areas burned by suspected overwintering fires, evaluating six spectral indices against their historical distributions to identify anomalies as potential fingerprints of elevated fire susceptibility. We identified 25 suspected overwintering fires, accounting for only 1.3% of the wildfires from 2024 but a disproportionate 22.8% of the total area burned. Relative to the reference period, pre-fire Normalized Difference Moisture Index (NDMI) was -0.0654 and Normalized Difference Vegetation Index (NDVI) was -0.1082. Similar patterns were identified in Green Normalized Difference Vegetation Index (GNDVI), Normalized Difference Water Index (NDWI), and SWIR-Transformed Reflectance (STR). Normalized Difference Snow Index (NDSI) was not substantially different from the reference period. Critically, we did not detect statistically significant differences between overwinter burned areas and comparable unburned areas in the same region, suggesting that conditions conducive to overwintering were widespread. These results suggest that multispectral imagery could be valuable as an early-warning system for the emerging threat of overwintering wildfires.

1. Introduction

The 2023 Canadian wildfire season was the worst on modern record, with almost 15 million hectares burned (Jain et al., 2024). Early-season drought persisted through the year across much of the boreal forest, contributing to an exceptional degree of deep, destructive peatland burning. These smouldering fires contrast with typical aboveground flaming fires, burning at rates of approximately 1 cm/hr and at temperatures of 500°C, compared to over 900°C in flaming combustion (Rein, 2013). This allows smouldering fires to burn deep underground in coarse woody debris and organic soils, potentially reemerging the following spring during a period where forest fuels are especially dry. These "overwintering" fires were especially prevalent in 2024, and contributed to substantial impacts to forest health, air quality, and human health and property. This phenomenon is difficult to observe with satellite remote sensing due to the low smouldering fire temperatures, small spatial footprint, and overlying snowpack (Rein and Huang, 2021).

Despite the increasing impacts of overwintering fires, we do not yet have an evidence-based method for predicting their occurrence or monitoring them once they begin. Autumn drought is known to be a contributing factor in spring wildfire activity (Hanes et al., 2020), but it is unknown how this knowledge can be operationalized to predict overwintering fire reemergence in the following spring. Previous studies of overwintering fires have suggested that overwintering occurs predominantly in deep, organic soils such as those present in peatlands (Scholten et al., 2021). However, recent evidence suggests that upland overwintering fires are just as common, with fires burning in tree roots and coarse woody debris (Baltzer et al., 2025). Overwinter fire occurrence is spatially and temporally autocorrelated, but it is unknown if this is predominantly due to bottom-up factors (e.g. wildfire fuels) or top-down factors (e.g. large-scale weather patterns). Most wildfires self-extinguish in the winter, but with an increasing record it may now be possible to build a predictive model of overwintering. Although the snowpack makes near-real-time monitoring of overwintering fires very difficult, post hoc analysis with remote sensing may reveal the conditions that are conducive to overwinter fire persistence. This has implications for frontline fire suppression crews and for boreal communities, including many northern and First Nations communities.

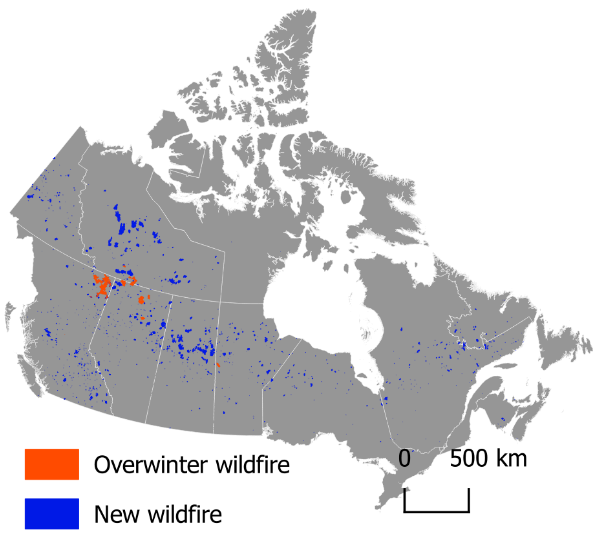

Figure 1. Study area. Polygons indicate Canadian 2024 wildfires as detected in the National Burned Area Composite (Skakun et al., 2022).

Remote sensing of pre-fire conditions can be used to predict fuel moisture content and fire danger (Akther and Hassan, 2011; Wilkinson et al., 2021). Some authors have found that, by incorporating seasonal trends or seasonal decomposition with remote sensing imagery, they attained a better estimate of landscape-level fire risk (Chuvieco et al., 2004; Pelletier et al., 2023). This may be valuable for predicting overwintering risk, given the importance of fuel moisture in contributing to overwintering fire initiation, including in both deep organic soils and in coarse woody debris (Baltzer et al., 2025; Wilkinson et al., 2019). Both microwave and multispectral imagery have applications for fuel moisture monitoring, but there is almost no published research on their use for specifically predicting overwinter fires. Given the high computational costs and complex calibration for applying microwave imagery, multispectral imagery represents a more accessible data stream for fire managers and researchers seeking to predict overwinter fires before they happen.

In this study we used multispectral imagery from Sentinel-2 to identify conditions associated with overwintering fires that burned in 2023 and reemerged in 2024. We identify overwintering fire through the intersection of fire polygon maps and thermal anomalies with atypical seasonality. We use non-parametric seasonal anomaly detection on pre-fire spectral index time series to extract temporal trends and anomaly patterns consistent with drought stress and heightened fire vulnerability leading into the 2024 fire season. Finally, we discuss remaining challenges and limitations to using multispectral index anomalies for overwinter fire vulnerability assessments.

2. Methodology

2.1 Overwinter fire detection

The study area for this study was the entirety of Canada for the 2023 and 2024 fire seasons (Figure 1), as limited by the mapped area of the National Burned Area Composite (NBAC, Skakun et al., 2022). This is approximately the forested extent bounded by the agricultural zones to the south and the taiga to the north. We downloaded all active fire detections / thermal anomalies (hereafter "hotspots") for 2023 and 2024 from the NASA Fire Information for Resource Management System (FIRMS) (NASA FIRMS, 2025), which includes both Moderate Resolution Imaging Spectroradiometer (MODIS) and Visible Infrared Imaging Radiometer Suite (VIIRS) detections. These hotspots were subset to include confidence values of nominal or high for VIIRS hotspots and a confidence rating of minimum 30% for MODIS hotspots.

Hotspots and NBAC polygons (>20 ha) were used to identify suspected overwintering fires that began in the 2023 fire season and reemerged in the 2024 spring fire season. Detecting overwintering fires with mid-winter hotspots is technically challenging and unreliable, given their low temperatures and the overlying snowpack (Xu et al., 2022). Therefore, differentiating new and overwintering fires depends on detecting early season hotspots, a period when there are generally no lightning-caused ignitions and fewer human-caused ignitions, especially far from populated areas (Coogan et al., 2020; Parisien et al., 2023). We took a conservative approach and identified suspected overwintering wildfires as 2024 NBAC polygons which intersect both early 2024 hotspots and late 2023 hotspots (Figure 2). Confirmed 2024 human-caused fires were removed from the dataset. Spring hotspots were considered anomalously early when they occurred before May 15, 2024, approximately the date associated with snowmelt in the southern edge of the western Boreal Plains region (Pickell et al., 2017).

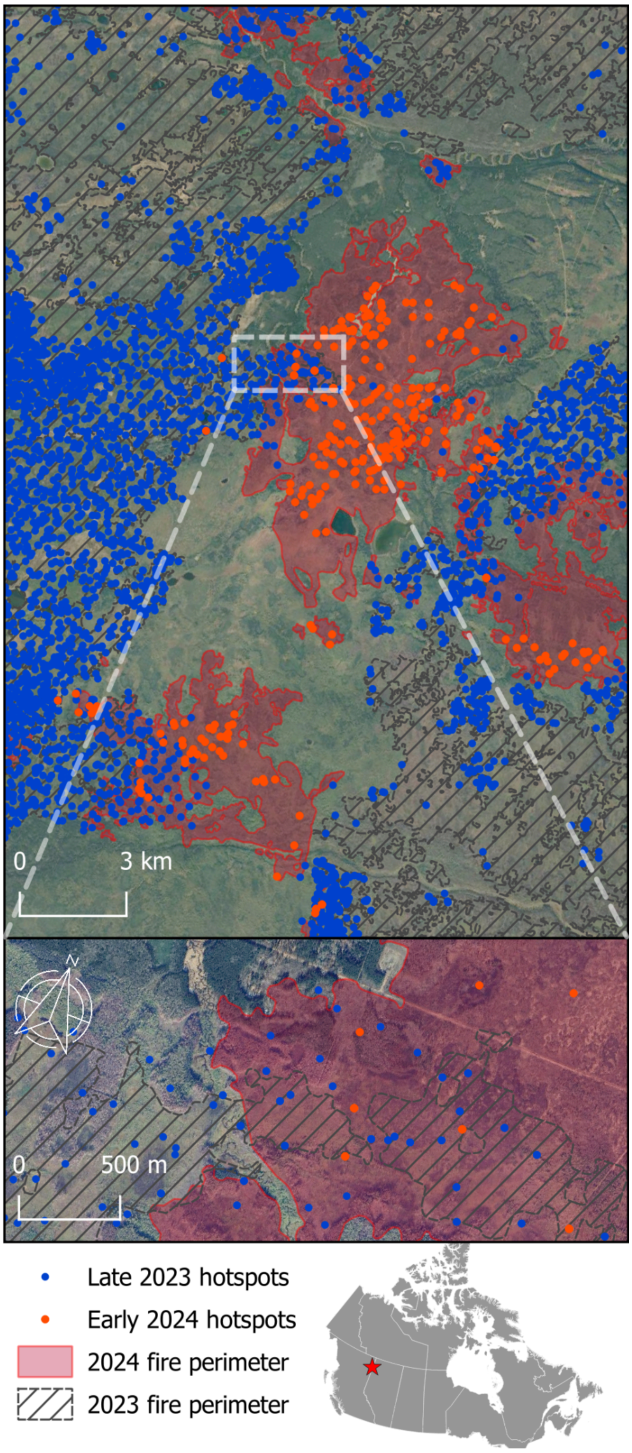

Figure 2. Overwintering NBAC fire ID 2024_183 with intersecting 2023 wildfires polygons. VIIRS and MODIS hotspots (NASA FIRMS, 2025) indicate 2023 hotspots from after September 15, 2023 ("Late hotspots") and 2024 hotspots from before May 15, 2024 ("Early hotspots").

Hotspots were considered seasonally late when detected after September 29, 2023. When both hotspots dataset overlap within a single 2024 fire polygon, that fire was considered as an overwinter fire. There is residual uncertainty around these being suitable threshold dates for identifying overwinter fires, therefore we conducted a sensitivity analysis by varying the threshold early- and late-detection dates by 2 weeks in either direction. This resulted in a change of <10% in the number of overwinter fires detected. Given that northern overwinter fires may have reemerged at a later date, this is considered a conservative estimate of the total number of overwinter fires.

2.2. Sentinel-2 Imagery and Processing

Harmonized Sentinel-2 MSI: MultiSpectral Instrument, Level-2A (SR) ("COPERNICUS/S2_SR_HARMONIZED") imagery was downloaded from Google Earth Engine for 2017 through 2025 for the identified overwinter fire polygons. Imagery was reduced to 16-day composites based on the lowest cloud coverage per 16-day period, and further filtered using the scene classification layer (SCL). We retained pixels with SCL values of 4, 5, 6, and 11, corresponding to vegetation, non-vegetation, water, and snow, thereby masking out all saturated, dark, shadowed, or cloudy pixels. Imagery from 2016 was not included due to the low number of observations associated with Sentinel-2A prior to the launch of Sentinel-2B.

Six spectral indices were tested for association with overwintering, including Normalized Difference Vegetation Index (NDVI), Eq. 1; green Normalized Difference Vegetation Index (GNDVI), Eq. 2; Normalized Difference Moisture Index (NDMI), Eq. 3; Normalized Difference Wetness Index (NDWI), Eq. 4; Normalized Difference Snow Index (NDSI), Eq. 5; and SWIR-Transformed Reflectance using Band 11 (STR11), Eq. 6. All spectral indices range from -1.0 to 1.0, except for STR which was not rescaled and varies from 0 to 8,095.

$$(1) \quad NDVI = \frac{(NIR - Red)}{(NIR + Red)}$$

$$(2) \quad GNDVI = \frac{(NIR - Green)}{(NIR + Green)}$$

$$(3) \quad NDMI = \frac{(NIR - SWIR)}{(NIR + SWIR)}$$

$$(4) \quad NDWI = \frac{(Green - NIR)}{(Green + NIR)}$$

$$(5) \quad NDSI = \frac{(Green - SWIR)}{(Green + SWIR)}$$

$$(6) \quad STR11 = \frac{(1 - SWIR)^2}{(2\, x\, SWIR)}$$

NDVI and GNDVI are both vegetation greenness indices, which have been used to monitor vegetation drought and fuel moisture content as detectable by declining NIR reflectance as stressed vegetation undergoes chlorosis and desiccation (Pettorelli et al., 2005, Yebra et al., 2008). NDMI is directly related to vegetation water content by the inverse relationship between SWIR reflectance and water content, making potentially a valuable early indicator of drought, especially in deciduous leaves and herbaceous plant matter (Gao, 1996). NDWI also correlates with vegetation water content, but its main application is for detecting open water (McFeeters, 1996). NDSI uses the difference between snow's high visible light reflectance and low SWIR reflectance to map snow cover (Salomonson and Appel, 2004). STR is a linearization of the SWIR response to soil moisture, with STR values inversely proportionate to soil moisture. STR is used in optical trapezoid methods (OPTRAM) (Sadeghi et al., 2015) but is also potentially useful on its own for broadscale moisture monitoring.

2.3 Anomaly Detection using *npphen*

We used the *npphen* R package (Chávez et al., 2022) to detect anomalies in our six indices prior to the identified overwintering fires, based on a baseline of 2017-2020. This method is part of a family of phenological trend/event detection methods, such as the *phenopix* R package (Filippa et al., 2016), which fits a parametric curve to remote sensing observations from a single growing season or multiple growing seasons. The *bfast* R package (Verbesselt et al., 2010) expands upon this by performing seasonal decomposition, whereby changes in spectral indices are decomposed into seasonal, trend, and remainder error components. In this way, anomalous signals in vegetation indices can be detected as departures from the seasonal pattern, a method that has also been applied in microwave remote sensing (Millard et al., 2022). However, many methods assume the seasonal component fits a regular, annual, parametric curve. *npphen* fits a curve based on the observed frequency of values with kernel density estimation, allowing the seasonal trend to take an irregular, non-parametric form.

The flexibility of *npphen* seasonal trend fitting is essential for anomaly detection across different spectral indices, which often follow a seasonal pattern but not necessarily a clean parametric curve. Where the seasonal trend from greenness indices such as NDVI or GNDVI is associated with phenological events such as leafout and leaf senescence, the trends associated with moisture indices such as NDMI may be less regular. Typically, moisture in the boreal is at a maximum following snowmelt and declines through the fire season, but this pattern may be spatially contextual. For example, peatlands in the Boreal Plains typically undergo a period of seasonal inundation associated with frozen soils, but the typical timing of this soil thaw is specific to individual peatlands and varies with latitude. Flexible methods such as *npphen* are necessary, since they can be used to evaluate moisture trends based on the historical distribution of index values for a given point. *npphen* model outputs include anomaly magnitude and anomaly significance, based on the values position within the reference frequency distribution.

We calculate anomalies for overwintering fires based on 5,000 points randomly distributed within the overwintering fire polygons, for the 2017 to 2025 period. The reference period of 2017-2020 was selected with a sensitivity analysis, in which it was found that the results were insensitive to a variable reference between three and seven years long. Three alternate experimental groups were established for statistical comparison against overwintering fires: one group of 10 random non-overwintering fires over 10,000 ha from all 2024 boreal fires; one group of unburned areas in the western boreal near major fire activity; and one group of unburned areas in the eastern boreal distant from major fire activity. All three additional test groups were used to generate 1,000 random points, for which 2017-2025 Sentinel-2 imagery was downloaded and processed as was done for overwintering fires. Mean anomaly values were compared with Kruskal–Wallis rank significance test. Mean anomaly values were summarized by spectral index and plotted as a time series across all sample points and pixel types.

All spatial and statistical processing was done in R version 4.5.0 (R Core Team, 2025). All Google Earth Engine scripting was done in Python version 3.12.7 (Python Software Foundation, 2025). Map production was done in QGIS version 3.42.2 (QGIS.org, 2026).

3. Results

Spatial analysis of wildfire and hotspots revealed that in 2024 overwintering wildfires burned an exceptionally large area relative to their overall frequency. Twenty-five overwinter fires were identified, counting complex fires only once. These fires corresponded to only 1.3% of the overall number of wildfires in Canada during 2024, but represented 22.8% of the overall area burned. This includes the Patry Creek wildfire from northeastern British Columbia, the single largest wildfire from 2024, which eventually burned over 450,000 ha.

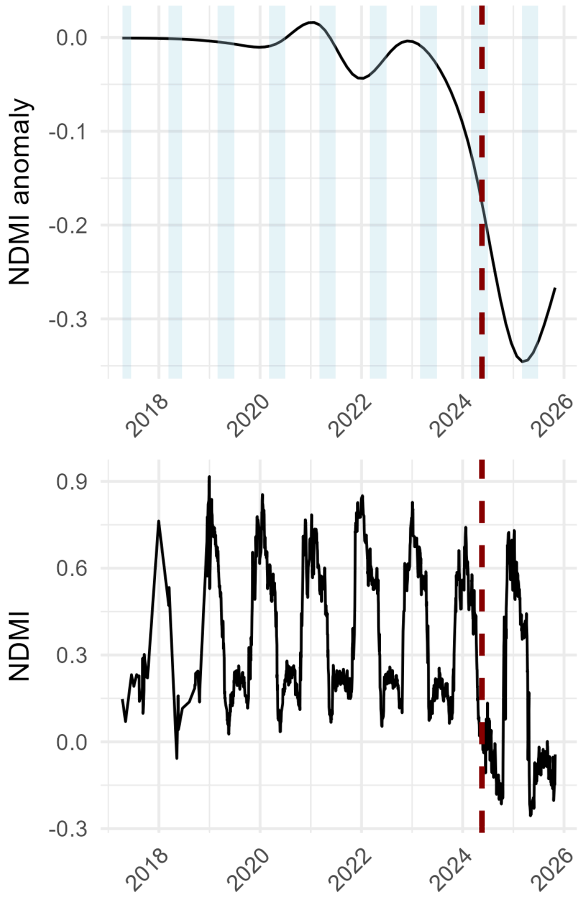

Figure 3. Raw NDMI and NDMI anomaly for 2017-2025 for overwintering 2023 wildfires. The red dashed line indicates the beginning of the 2024 wildfire season.

Overwintering wildfires were predominantly located in the western boreal forest between British Columbia, Alberta, and Northwest Territories, except for one overwintering wildfire near Flin Flon, SK. Sentinel 2 imagery analysis with *npphen* revealed a period of negative NDMI anomalies and positive STR anomalies for one year prior to the 2024 fires (Table 1, Figure 3). Similarly, both NDVI and GNDVI were anomalously low prior to the 2024 fires, indicating dry vegetation or a delay in vegetation greenup. NDSI values were slightly above seasonal norms. NDWI was substantially above seasonal norms, potentially indicating above average surface water, possibly from waterlogged soils or snowmelt inundation. Anomalies did not extend back to 2022, suggesting that the 2023 anomalies, in particular NDMI, NDVI, and GNDVI, may correspond to elevated overwinter fire risk. Extreme anomaly values from 2024 were likely associated with reflectance changes from burned areas and are not a realistic indicator of elevated overwinter fire risk. Kruskal–Wallis significance tests revealed that NDMI anomalies were significantly more negative for overwintering fires, non-overwintering fires, and unburned eastern boreal areas, than for unburned western boreal areas (Figure 4). NDVI and GNDVI anomalies from overwintering fires were not significantly lower than other experimental groups, while new 2024 wildfires had the lowest greenness of all four groups. The within-group variability of index anomalies exceeded the between-group variability, for all indices. This variable, but unidirectional response suggests that most variability in greenness and moisture indices was exhibited at a fine scale, and that landscape-level drought affected all cover classes, not areas with overwintering fires.

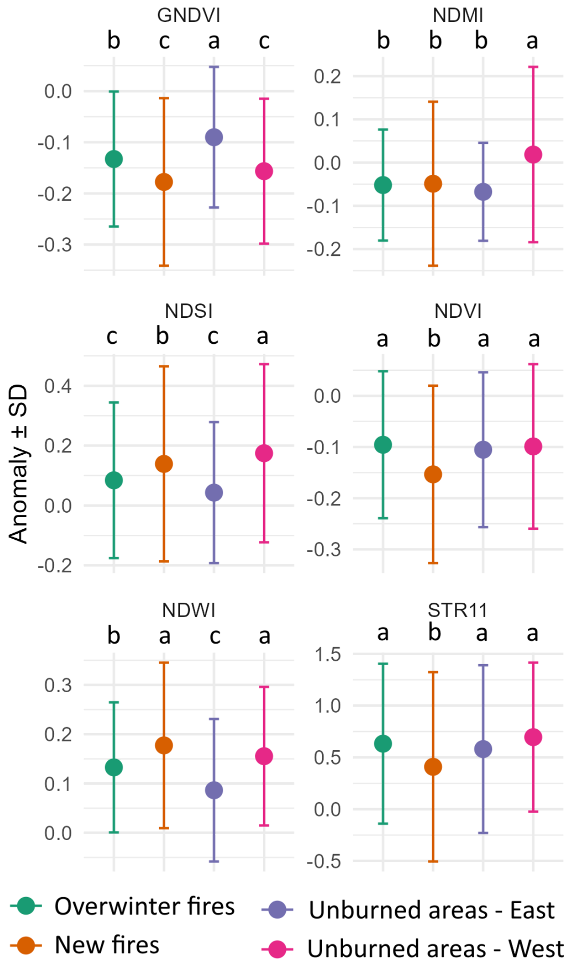

Figure 4. Mean anomaly values (mean+/-sd) for 2024 overwinter fires for 6 evaluated indices. Indices evaluated over 1 year period prior to fire, excluding December to March. Kruskal–Wallis significance values indicated with letters.

Table 1. Mean anomaly in Sentinel 2 indices for 1 year prior to overwintering fires, compared against the 2017-2020 reference period for 5000 sample points.

Index	Prefire anomaly
NDMI	-0.0654 +/- 0.1752
NDVI	-0.1082 +/- 0.2071
GNDVI	-0.1180 +/- 0.1932
NDSI	0.0800 +/- 0.2963
NDWI	0.1180 +/- 0.1932
STR11	53.69 +/- 226.87

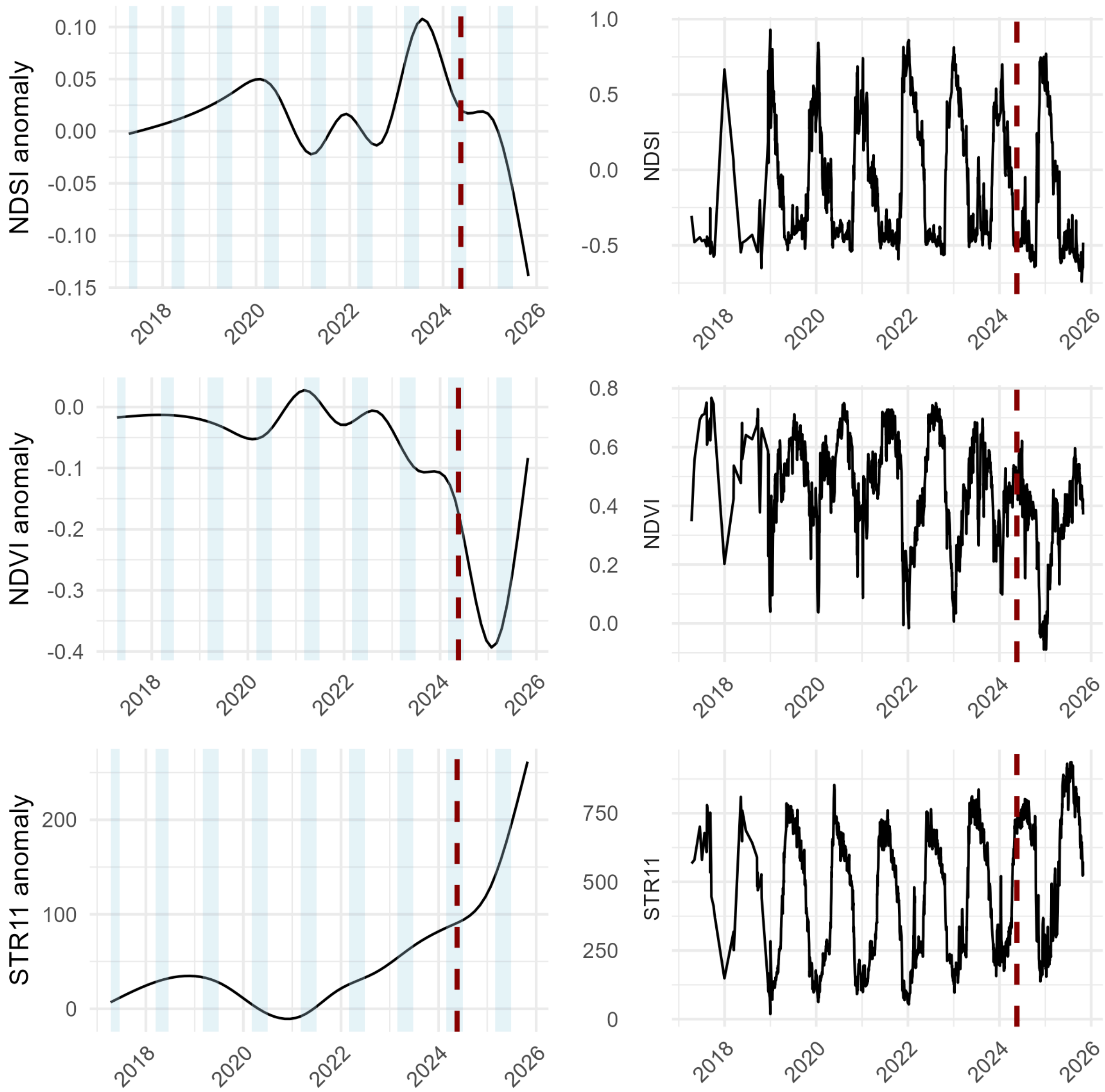

Figure 5. NDSI, NDVI, and STR11 anomaly and raw indices for 2017-2025 for overwintering 2023 wildfires. Red dashed line indicates the beginning of the 2024 wildfire season.

4. Discussion

The anomalies observed in Sentinel-2 imagery were well aligned with conditions reported by fire management agencies and media sources, which both report extensive overwintering in areas under severe drought conditions. These drought conditions were revealed in the NDMI anomalies, indicating a moisture deficit which likely contributed to the extensive spring burning. However, a lack of significant difference between the anomalies in overwintering areas as compared to other areas suggests that these signals may be of limited use for predicting the precise spatial location of overwinter fire activity, only the regional trends.

Our findings are in line with those of Pelletier et al. (2023), who found that the strongest predictor of peatland fires was multispectral moisture-related indices (tasseled cap wetness and NDMI). Previous studies found an association between moisture deficits and deep organic soil smoldering, leading to the assumption that these soils were the overwintering fuels for most overwinter wildfires (Scholten et al., 2021). Recent evidence suggests that coarse woody debris and tree roots, both in uplands and peatlands, may represent a substantial component of overwinter fire (Baltzer et al., 2025). Our findings cannot corroborate or refute these statements, since the exact overwintering location and medium is still unknown, and our observed anomalies spanned uplands and lowlands.

Seasonal variation in boreal forest fire probability is associated with boreal mixedwood stands where seasonally cured broadleaf and herbaceous fuels carry early-season fire. The western boreal forest exhibits the strongest spring fire seasonality, putting it at greatest vulnerability to overwinter fires (Parisien et al., 2023). Our findings suggest the early fire season in the western boreal, discussed in Parisien et al. (2023), and Magnussen and Taylor (2012), may be intensified by an increasing number of overwinter fires if climate change increases the regional moisture deficit as was observed in 2024.

The association of autumn drought with elevated fire activity the following spring was observed in Hanes et al. (2020). Our findings reinforce these observations, and we further add that autumn greenness anomalies may indicate another indicator of landscape-level vulnerability to overwintering. Our findings were also in agreement with their conclusion that winter precipitation was not a driver of spring fire likelihood, since we did not observe a negative NDSI anomaly over the 2023-2024 winter (Figure 5). However, NDSI is best understood as a proxy for snow cover extent. Therefore our findings may not capture the important effects of snowmelt timing and magnitude, which are better assessed using meteorological data and snowpack depth observations.

Greenness indices have long enjoyed use in fire vulnerability monitoring, such as the use of NDVI for vegetation moisture content remote sensing (Paltridge and Barber, 1988). This relationship was found to be weaker when assessing woody vegetation compared with herbaceous vegetation (Yebra et al., 2008). NDVI anomalies (Figure 5) may therefore be a valuable information source for predicting overwintering drought in regions where there are abundant herbaceous grasses and deciduous trees. This includes the Boreal Plains ecozone, where many of the observed overwintering fires occurred.

Some challenges remain in applying multispectral remote sensing data to wildfire prediction, which represent opportunities for further research. Differences between vegetation cover types are still poorly understood, especially seasonal moisture variability in closed-canopy conifer forests and forested peatlands. Also, it has yet to be established whether drought conditions in peatlands, uplands, or both contribute more substantially to overwinter activity. The spatial arrangement of overwintering fires and land cover types has yet to be investigated. This would require precise overwintering locations, which are not practical to achieve with satellite imagery alone due to the spatial resolutions required. Finally, it is unclear what suitable reference period should be used for time series analysis, especially under a changing climate. Our uncertainty analysis indicated that, at least for NDMI anomalies, the precise selection of the reference period did not overly affect our results (Table 2).

Table 2. Uncertainty analysis. Anomaly magnitude for NDVI, NDMI, STR when using different reference periods and different analysis periods before fire

Reference period	Mean Prefire NDMI Anomaly
2017-2018	-0.0513
2017-2019	-0.0509
2017-2020	-0.0664
2017-2021	-0.0599
2017-2022	-0.0570

It is necessary to acknowledge several limitations of this approach, chiefly associated with uncertainty around overwintering fires. First, it is unclear if overwintering fires are driven by moisture deficits, or merely correlated with them. All metrics based on observing soil and ground litter moisture are limited by the inability of multispectral imagery to see through canopy vegetation. For example, soil moisture monitoring methods are generally not recommended for canopy closures above 50% (Burdun et al., 2023), limiting our ability to directly monitor peatland soil surface in forested peatlands. Finally, this analysis represents an exploratory sample using a single year, albeit one with record-breaking overwintering behaviour. To generalize this method it will be necessary to expand the test period to include several more years, including those with few overwinter fires.

5. Conclusions

Our method for identifying overwintering wildfires is based on the intersection of mapped fire perimeters and unusually early thermal hotspots the following spring. We identified 25 suspected overwintering wildfires from the Canadian 2023-2024 fire season, which constituted only 1.3% of all fires but 22.8% of the overall area burned. The overwintering fires were associated with pre-fire anomalies in Sentinel-2 multispectral indices, including NDMI, NDVI, and GNDVI. These anomalies may have value as an early-warning system for regional overwintering fire risk, which may be explored in future work.

References

Akther, M.S., Hassan, Q.K., 2011. Remote Sensing-Based Assessment of Fire Danger Conditions Over Boreal Forest. IEEE J. Sel. Top. Appl. Earth Obs. Remote Sens. 4, 992–999. https://doi.org/10.1109/JSTARS.2011.2165940

Baltzer, J.L., Walker, X.J., Veraverbeke, S., Hessilt, T.D., Alfaro-Sanchez, R., Van Gerrevink, M.J., Mack, M.C., Ogden, E.L., Olsen, R., Scholten, R.C., Turetsky, M.R., 2025. Overwintering fires can occur in both peatlands and upland forests with varying ecological impacts. Nat. Ecol. Evol. 9, 559–564. https://doi.org/10.1038/s41559-024-02630-2

Burdun, I., Bechtold, M., Aurela, M., De Lannoy, G., Desai, A.R., Humphreys, E., Kareksela, S., Komisarenko, V., Liimatainen, M., Marttila, H., Minkkinen, K., Nilsson, M.B., Ojanen, P., Salko, S.-S., Tuittila, E.-S., Uuemaa, E., Rautiainen, M., 2023. Hidden becomes clear: Optical remote sensing of vegetation reveals water table dynamics in northern peatlands. Remote Sens. Environ. 296, 113736. https://doi.org/10.1016/j.rse.2023.113736

Chávez, R.O., Estay, S.A., Lastra, J.A., Riquelme, C.G., Olea, M., Aguayo, J., Decuyper, M., 2022. npphen: An R-Package for Detecting and Mapping Extreme Vegetation Anomalies Based on Remotely Sensed Phenological Variability. Remote Sens. 15, 73. https://doi.org/10.3390/rs15010073

Chuvieco, E., Cocero, D., Riaño, D., Martin, P., Martínez-Vega, J., de la Riva, J., Pérez, F., 2004. Combining NDVI and surface temperature for the estimation of live fuel moisture content in forest fire danger rating. Remote Sens. Environ., Forest Fire Prevention and Assessment 92, 322–331. https://doi.org/10.1016/j.rse.2004.01.019

Coogan, S.C.P., Cai, X., Jain, P., Flannigan, M.D., 2020. Seasonality and trends in human- and lightning-caused wildfires ≥ 2 ha in Canada, 1959–2018. Int. J. Wildland Fire 29, 473–485. https://doi.org/10.1071/WF19129

Filippa, G., Cremonese, E., Migliavacca, M., Galvagno, M., Forkel, M., Wingate, L., Tomelleri, E., Morra Di Cella, U., Richardson, A.D., 2016. Phenopix: A R package for image-based vegetation phenology. Agric. For. Meteorol. 220, 141–150. https://doi.org/10.1016/j.agrformet.2016.01.006

Gao, B., 1996. NDWI—A normalized difference water index for remote sensing of vegetation liquid water from space. Remote Sens. Environ. 58, 257–266. https://doi.org/10.1016/S0034-4257(96)00067-3

Hanes, C., Wotton, M., Woolford, D.G., Martell, D.L., Flannigan, M., 2020. Preceding Fall Drought Conditions and Overwinter Precipitation Effects on

Spring Wildland Fire Activity in Canada. Fire 3, 24. https://doi.org/10.3390/fire3020024

Jain, P., Barber, Q.E., Taylor, S.W., Whitman, E., Castellanos Acuna, D., Boulanger, Y., Chavardès, R.D., Chen, J., Englefield, P., Flannigan, M., Girardin, M.P., Hanes, C.C., Little, J., Morrison, K., Skakun, R.S., Thompson, D.K., Wang, X., Parisien, M.-A., 2024. Drivers and Impacts of the Record-Breaking 2023 Wildfire Season in Canada. Nat. Commun. 15, 6764. https://doi.org/10.1038/s41467-024-51154-7

Magnussen, S., Taylor, S.W., 2012. Inter- and intra-annual profiles of fire regimes in the managed forests of Canada and implications for resource sharing. Int. J. Wildland Fire 21, 328–341. https://doi.org/10.1071/WF11026

McFeeters, S.K., 1996. The use of the Normalized Difference Water Index (NDWI) in the delineation of open water features. Int. J. Remote Sens. 17, 1425–1432. https://doi.org/10.1080/01431169608948714

Millard, K., Darling, S., Pelletier, N., Schultz, S., 2022. Seasonally-decomposed Sentinel-1 backscatter time-series are useful indicators of peatland wildfire vulnerability. Remote Sens. Environ. Accepted, In press.

NASA FIRMS, 2025. Fire Information for Resource Management System.

Paltridge, G.W., Barber, J., 1988. Monitoring grassland dryness and fire potential in australia with NOAA/AVHRR data. Remote Sens. Environ. 25, 381–394. https://doi.org/10.1016/0034-4257(88)90110-1

Parisien, M., Barber, Q.E., Flannigan, M.D., Jain, P., 2023. Broadleaf tree phenology and springtime wildfire occurrence in boreal Canada. Glob. Change Biol. 29, 6106–6119. https://doi.org/10.1111/gcb.16820

Pelletier, N., Millard, K., Darling, S., 2023. Wildfire likelihood in Canadian treed peatlands based on remote-sensing time-series of surface conditions. Remote Sens. Environ. 296, 113747. https://doi.org/10.1016/j.rse.2023.113747

Pettorelli, N., Vik, J.O., Mysterud, A., Gaillard, J.-M., Tucker, C.J., Stenseth, N.Chr., 2005. Using the satellite-derived NDVI to assess ecological responses to environmental change. Trends Ecol. Evol. 20, 503–510. https://doi.org/10.1016/j.tree.2005.05.011

Pickell, P.D., Coops, N.C., Ferster, C.J., Bater, C.W., Blouin, K.D., Flannigan, M.D., Zhang, J., 2017. An early warning system to forecast the close of the spring burning window from satellite-observed greenness. Sci. Rep. 7, 14190. https://doi.org/10.1038/s41598-017-14730-0

Python Software Foundation. 2025. *Python* (Version 3.12.7). Python Software Foundation.

QGIS Development Team. 2025. *QGIS Geographic Information System* (Version 3.42.2). Zenodo. https://doi.org/10.5281/zenodo.15241389

R Core Team. 2025. *R: A language and environment for statistical computing* (Version 4.5.0). R Foundation for Statistical Computing. R Project for Statistical Computing

Rein, G., 2013. Smouldering Fires and Natural Fuels, in: Belcher, C.M. (Ed.), Fire Phenomena and the Earth System. Wiley, pp. 15–33. https://doi.org/10.1002/9781118529539.ch2

Rein, G., Huang, X., 2021. Smouldering wildfires in peatlands, forests and the arctic: Challenges and perspectives. Curr. Opin. Environ. Sci. Health 24, 100296. https://doi.org/10.1016/j.coesh.2021.100296

Sadeghi, M., Jones, S.B., Philpot, W.D., 2015. A linear physically-based model for remote sensing of soil moisture using short wave infrared bands. Remote Sens. Environ. 164, 66–76. https://doi.org/10.1016/j.rse.2015.04.007

Salomonson, V.V., Appel, I., 2004. Estimating fractional snow cover from MODIS using the normalized difference snow index. Remote Sens. Environ. 89, 351–360. https://doi.org/10.1016/j.rse.2003.10.016

Scholten, R.C., Jandt, R., Miller, E.A., Rogers, B.M., Veraverbeke, S., 2021. Overwintering fires in boreal forests. Nature 593, 399–404. https://doi.org/10.1038/s41586-021-03437-y

Skakun, R., Castilla, G., Metsaranta, J., Whitman, E., Rodrigue, S., Little, J., Groenewegen, K., Coyle, M., 2022. Extending the National Burned Area Composite Time Series of Wildfires in Canada. Remote Sens. 14, 3050. https://doi.org/10.3390/rs14133050

Verbesselt, J., Hyndman, R., Newnham, G., Culvenor, D., 2010. Detecting trend and seasonal changes in satellite image time series. Remote Sens. Environ. 114, 106–115. https://doi.org/10.1016/j.rse.2009.08.014

Wilkinson, S.L., Furukawa, A.K., Wotton, B.M., Waddington, J.M., 2021. Mapping smouldering fire potential in boreal peatlands and assessing interactions with the wildland–human interface in Alberta, Canada. Int. J. Wildland Fire 30, 552–563. https://doi.org/10.1071/WF21001

Wilkinson, S.L., Moore, P.A., Waddington, J.M., 2019. Assessing Drivers of Cross-Scale Variability in Peat Smoldering Combustion Vulnerability in Forested Boreal Peatlands. Front. For. Glob. Change 2.

Xu, W., Scholten, R.C., Hessilt, T.D., Liu, Y., Veraverbeke, S., 2022. Overwintering fires rising in eastern Siberia. Environ. Res. Lett. 17, 045005. https://doi.org/10.1088/1748-9326/ac59aa

Yebra, M., Chuvieco, E., Riaño, D., 2008. Estimation of live fuel moisture content from MODIS images for fire risk assessment. Agric. For. Meteorol. 148, 523–536. https://doi.org/10.1016/j.agrformet.2007.12.005