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Research article

Assessing the NDDI Drought Index Using the Google Earth Engine for Peat Fire Risk Monitoring in Siak, Indonesia

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Abstract

Peatland ecosystems across tropical regions are prone to severe fires during drought periods, making timely and accurate early drought monitoring vital for fire risk mitigation. This study assesses drought conditions in Siak Regency, Indonesia, employing the Normalized Difference Drought Index (NDDI) derived from Sentinel-2 satellite imagery using the Google Earth Engine (GEE) platform. NDDI, which combines indices of vegetation greenness (NDVI) and moisture (NDWI), was used to map peatland dryness. The research analysed NDDI patterns for each month from 2019 to 2024 and was tested against MODIS and VIIRS fire hotspots both spatially, by overlaying hotspots on classified drought maps, and temporally, using Spearman correlation. The results show that the two approaches produced an informative contrast. Spatially, fire was concentrated strongly in the driest classes: on average 91% of hotspots (85% pooled across all 507 detections made) fell within the severe and extreme drought classes (NDDI > 0.25). A chi-square test confirmed that this distribution was clearly not a question of chance (chi-square = 96.1, p < 0.001). Temporally, however, the month-to-month correlation was weak (mean rho = 0.24), so the surface signal alone does not set fire timing within a particular year. An independent CHIRPS rainfall record confirmed the wet- and dry-year ranking and linked annual rainfall to burnt areas (rho = -0.94, p = 0.005). NDDI is therefore a reliable indicator of areas where peatland is fire-prone, and is best used as a spatial fire-susceptibility layer within a multi-factor early-warning system, being transferable to other tropical peatlands.

Keywords: Drought Index; Google Earth Engine; Hotspot; NDDI; Peat Fire; Sentinel-2

1. Introduction

Tropical peatlands are naturally waterlogged ecosystems that store large amounts of carbon and in the past have rarely burnt (Yusa *et al.*, 2019). However, over the past few decades, they have become highly fire-prone due to land-use conversion accompanied by canal construction for drainage (Kiely *et al.*, 2021; Yokelson *et al.*, 2022). Forest loss and extensive drainage canal constructions for agriculture and plantations have lowered groundwater levels, drying soils that are typically inundated and thereby increasing their risk to fire (Sukma & Sutikno, 2025; Sutikno *et al.*, 2020; Putra *et al.*, 2019). In Indonesia, peatland fires occur almost every year during the dry season (Mezbahuddin *et al.*, 2023; Sutikno *et al.*, 2026). Prolonged drought often associated with the El Niño phenomenon reduces peat moisture and groundwater levels, creating conditions that are highly conducive to burning (Mezbahuddin *et al.*, 2023; Bruno *et al.*, 2025). Extreme drought conditions in 2015 and 2019 led to widespread peatland fires across Sumatra and Kalimantan, causing severe environmental and public health impacts (Grosvenor *et al.*, 2024; Wee *et al.*, 2023; Graham *et al.*, 2024; Hayasaka, 2023). The extended El Niño-driven dry season in 2019 triggered large-scale peat fires that blanketed the region with hazardous haze and was associated with health impacts affecting approximately 87,000 people across Indonesia due to exposure to fine particulate matter ($PM_{2.5}$) (Grosvenor *et al.*, 2024; Hamdi *et al.*, 2025). This situation demonstrates that peat fire mitigation efforts require a robust early warning system based on drought monitoring with high temporal and spatial accuracy (Mezbahuddin *et al.*, 2023).

Drought is commonly defined as a temporary, recurrent deficit of water relative to normal conditions, of sufficient magnitude and duration to affect ecosystems, agriculture or society, and is distinguished from aridity, which is a permanent climatic feature (Wilhite & Glantz, 1985). In peatlands, it is the vegetation and near-surface moisture component of this deficit, rather than the rainfall deficit itself, that most directly governs fire risk. Drought indices, which reflect a lack of moisture, have the potential to be used as indicators of forest and land fire risk levels. The index commonly used to correlate with peatland fire risk levels is the Standard Precipitation Index (SPI) (Sukma & Sutikno, 2025; Vicente-Serrano *et al.*, 2012; Sutikno *et al.*, 2020). However, the SPI is typically calculated from point-based observations and may not fully capture the spatial patterns of surface dryness across heterogeneous peatland landscapes. Satellite remote sensing offers an alternative approach for large-scale, near-real-time drought monitoring (Affandy *et al*., 2024; Sánchez Alcalde & Escorihuela, 2025). Vegetation indices derived from satellite data, particularly from moderate- to high-resolution sensors, can be used as indicators of on-the-ground drought conditions by directly detecting changes in vegetation status and surface moisture.

One commonly used approach is the Normalized Difference Vegetation Index (NDVI), which measures vegetation greenness and canopy density. NDVI values tend to fall under drought stress because chlorophyll content and leaf area decrease (Hajek *et al*., 2024; Vukadinović *et al*., 2025). Similarly, the Normalized Difference Water Index (NDWI), which reflects vegetation water content or surface moisture, typically decreases as soils lose moisture (Chandrasekar *et al*., 2024). By combining these two indices, the Normalized Difference Drought Index (NDDI) has been proposed as a remote-sensing indicator of drought (Affandy *et al*., 2024). NDDI integrates NDVI and NDWI to jointly account for vegetation health and moisture conditions, highlighting vegetation water deficits. Gu *et al*. (2007) originally introduced NDDI for grassland drought assessment, and more recent studies have demonstrated its effectiveness across diverse environments. For example, NDDI has been applied to track agricultural drought in arid regions and has been shown to capture rainfall deficits and associated impacts on crop yield. A 2023 study in farmlands along the Gulf of Mexico concluded that Landsat-8–based NDDI is a powerful indicator for quantifying drought intensity, showing strong correlations with conventional drought metrics during the dry season (Salas-Martínez *et al*., 2023). Likewise, Patil *et al*. (2024) demonstrated the utility of NDDI for drought assessment in semi-arid regions of India, while a case study in Indonesia reported that NDDI can effectively map agricultural drought stress in croplands on Java. The index ranges from −1 to +1, with higher positive values indicating more severe drought (e.g., NDDI > 0.3 indicates extreme drought), while negative values correspond to water saturated areas (Cheng *et al*., 2024).

Nevertheless, the application of NDDI for drought monitoring in peatlands remains very limited. Such terrain presents unique challenges because fire risk is not driven solely by surface vegetation dryness, but also by subsurface peat moisture and groundwater table depth (Mezbahuddin *et al*., 2023; Taufik *et al*., 2023; Putra *et al*., 2019). Therefore, conventional drought indices based on rainfall may not accurately predict soil surface moisture, especially for deeper peat soils. In this case, NDDI, as a surface-based drought indicator, can provide an indirect estimate of peat moisture conditions, which can serve as an early warning signal for peatland fire risk.

Our research was conducted in Siak Regency, Riau Province, Indonesia, an area dominated by tropical peatlands which frequently experiences fires during the dry season. The area is a major contributor to haze disasters in Riau Province. Previous similar research in the regency found that fire risk is high when the meteorological drought index is SPI < -1.5 (Sukma & Sutikno, 2025). To exploit this, Sentinel-2 multispectral imagery, which provides 10–20 m spatial resolution and 5-10 day temporal resolution (Varghese *et al*., 2021; Wu *et al*., 2023), was used and processed through the Google Earth Engine (GEE) cloud platform. Efficient derivation of NDVI, NDWI and NDDI time series over large areas without local computational constraints is made possible by GEE's combination of petabyte-scale data archives and server-side computation, making it well-suited to operational monitoring tasks (Tamiminia *et al*., 2020; Thottolil & Kumar, 2018).

Based on the above background, the study aims to: (1) conduct a spatial and temporal analysis of the NDDI drought index across tropical peatlands in Siak Regency during the period 2019 to 2024; (2) validate the index against observed peat fire occurrence, both spatially and temporally, and against an independent rainfall record; and (3) evaluate the potential of NDDI as an indicator to support peatland fire early-warning and water management.

2. Methods

2.1 Region of Study

Siak Regency is located in Riau Province, Sumatra, Indonesia, and encompasses extensive peatland areas. The region lies roughly between 0°45’–1°30’ N and 101°50’–102°50’ E (Figure 1), and is characterised by a tropical rainforest climate with a bimodal rainfall pattern. Rainfall peaks typically occur in November to December, with a pronounced dry season from June to September (Hayasaka, 2023). Average annual rainfall exceeds 2000 mm, but drought severity intensifies during El Niño years, when the June to September dry season becomes hotter and longer. The flat, low-lying terrain is underlain by thick peat deposits (in places >5 m deep), especially in coastal and riverine areas (Wahyunto *et al*., 2003). These peat soils store enormous carbon stocks but become highly flammable when dried (Page *et al*., 2002). Land cover in Siak includes peat swamp forests (both intact and degraded), acacia and oil palm plantations on peat, and smallholder agriculture (Wee *et al*., 2023). Over the past decades, drainage for agriculture and forestry plantations has lowered peat water tables, increasing the susceptibility of the area to drought and fire (Kiely *et al*., 2021; Mezbahuddin *et al*., 2023). Siak has experienced frequent peat and forest fires, with significant events recorded in 2015 and 2019 in line with regional droughts (Grosvenor *et al*., 2024). This combination of climatic and anthropogenic factors makes Siak an ideal case for drought index assessment in a peat fire context.

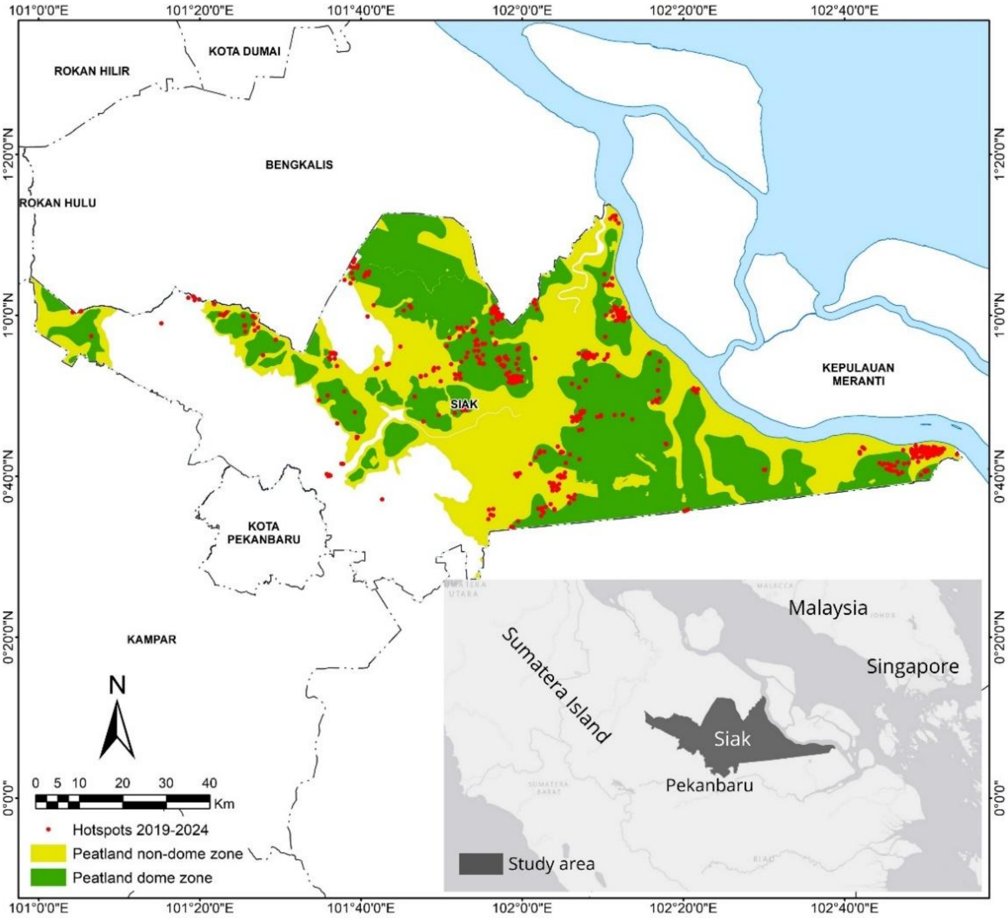


Figure 1. Siak Regency, Riau Province, Indonesia, with approximately 80% of its territory consisting of peatlands. The map delineates peat dome areas and non-dome peatland zones and overlays all fire hotspots detected between 2019 and 2024 (red points). Siak's peatlands lie in lowland tropical rainforest terrain and have been partly drained for plantations, making them vulnerable to drying and fires.

2.2 Data and Tools

The research used Sentinel-2 multispectral imagery as the primary data source for computing NDVI, NDWI and NDDI. Sentinel-2A and 2B (operated by ESA) provide 10 m resolution data in the visible and near-infrared bands and 20 m resolution in shortwave infrared bands (useful for moisture indices) (Wu *et al*., 2023; Islam & Ahamed, 2023). The focus was on the dry season months from 2019 to 2024 in order to capture critical periods of peatland drying. Cloud-free or minimal cloud images for each month in the June–September period were selected, with the imagery accessed and processed via Google Earth Engine (GEE). Using GEE's JavaScript API, the Sentinel-2 Level-2A image collection was filtered by date, region (Siak Regency boundary), and cloud cover (<20%). Cloud/cloud-shadow masking was applied using the Sentinel-2 quality bands and temporal mosaicking to ensure clear observations. The resulting images were converted to surface reflectance and employed to compute the indices.

GEE tools were used to analyse and extract geospatial information from the Sentinel-2 satellite imagery. The analytical workflow included data filtering, index computation and other spatial analyses (Rufin *et al*., 2021). Using this approach, calculations can be performed rapidly on large-volume datasets without requiring high-end local computing resources. Employing GEE, scripts were developed to implement key steps such as data filtering, cloud masking, index calculation and time-series analysis. Overall, GEE significantly accelerated the workflow, enabling on-demand updates of drought indices and fast, reproducible analyses.

To relate drought patterns with fire incidence, fire hotspot and burn scar data were obtained for the study region. Active fire detection data were also acquired from NASA's Fire Information for Resource Management System (FIRMS), which provides daily fire hotspot coordinates detected by the MODIS and VIIRS satellite sensors. The FIRMS hotspot dataset was filtered for points within Siak Regency during the period 2019–2024, focusing on the dry-season months. Each hotspot is a georeferenced location of active fire with a timestamp. In addition, any available burnt-area information was gathered to validate fire-affected zones; for example, Sentinel-2-derived burn scar maps from Indonesia's Ministry of Environment, or global burn area products. These fire data were used to identify when and where significant peat fires occurred, and to compare them with the timing and location of drought conditions indicated by NDDI. To support contextual interpretation, a land-cover classification, a peat soil distribution and dome-depth map, monthly rainfall records from local meteorological stations, and satellite-based precipitation estimates (CHIRPS, Climate Hazards Group InfraRed Precipitation with Station data) were compiled. The CHIRPS data were used to verify periods classified as drought by NDDI and to cross-check against published SPI values for the Riau region. Figure 2 presents the overall analytical workflow, from data acquisition, to drought mapping and fire risk assessment.

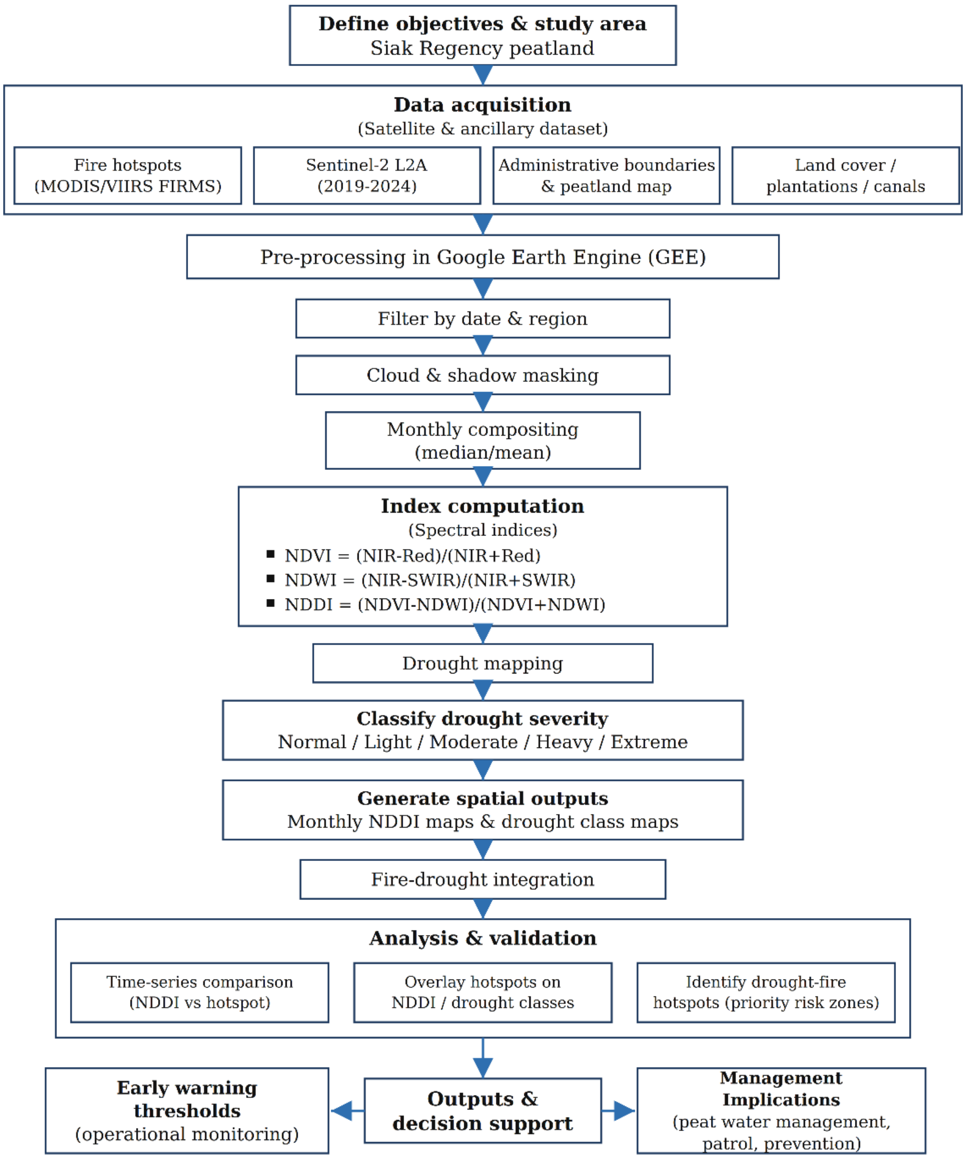


Figure 2. Conceptual research framework and flowchart for assessing the drought index using NDDI and Google Earth Engine for peat fire risk monitoring in Siak, Indonesia

2.3. Analysis Techniques

NDVI and NDWI were calculated for each selected Sentinel-2 image (or monthly composite) on a per-pixel basis. Following Peng & Gong (2025), NDVI is defined as Equation 1. Where *NIR* is the reflectance in the near-infrared band (Sentinel-2 band 8 at 842 nm) and *Red* is the reflectance in the red band (band 4 at 665 nm). NDVI values range from –1 to +1, with higher values indicating dense, healthy vegetation.

$$NDVI = \frac{NIR-Red}{NIR+Red} \tag{1}$$

NDWI has multiple formulations in previous research; in our case, the version sensitive to vegetation water content (Equation 2) is adopted (Gao, 1996). Where *SWIR* is a shortwave infrared band. Sentinel-2's SWIR band 11 (1610 nm) was used for this purpose, as it is commonly used to detect moisture in vegetation canopies and soils (Salas-Martínez *et al*., 2023). NDWI yields higher values for water-rich surfaces (and open water bodies) and lower values for dry surfaces.

$$NDWI = \frac{NIR-SWIR}{NIR+SWIR}, \tag{2}$$

On the other hand, the NDDI was derived for each pixel and date. Equation 3 was used to compute the NDDI (Gu *et al*., 2007; Affandy *et al*., 2024). This formulation produces an index in which positive values indicate vegetation stress (reduced greenness or low moisture) associated with drought, whereas negative NDDI values typically correspond to wet or water-covered pixels (where NDWI is high, or NDVI is low due to open water) (Cheng *et al*., 2024).

$$NDDI = \frac{NDVI-NDWI}{NDVI+NDWI}. \tag{3}$$

In practice, a simpler form that is sometimes used in related research was also considered: NDDI ≈ NDVI − NDWI (Affandy *et al*., 2024), which is proportional to the formal ratio above for moderate index ranges. It was verified that the choice of formulation does not significantly alter the spatial patterns of drought-prone hotspots. All index calculations were performed in GEE on a per-pixel basis for each date. To reduce noise, particularly in areas with residual cloud contamination, monthly index values were aggregated using the median.

Drought severity was classified using threshold ranges adapted from Firdaus *et al*. (2024), who applied NDDI for rice-paddy drought monitoring in Indonesia, with minor adjustments to reflect peatland hydrological characteristics. The resulting five classes were: Normal (NDDI < 0.01), Light drought (0.01 ≤ NDDI < 0.15), Moderate drought (0.15 ≤ NDDI < 0.25), Severe drought (0.25 ≤ NDDI < 1.0), and Extreme drought (NDDI > 1.0). For each monthly map, the area extent of each drought class was quantified in square kilometres and as a percentage of the total peatland area.

The temporal analysis examined mean NDDI across Siak for each month in the period 2019 and 2024, allowing us to identify the timing and intensity of drought episodes year by year. These NDDI time series were compared against monthly rainfall anomalies and the fire-hotspot record to assess whether drought peaks preceded fire peaks, and if so by how long. Fire hotspot locations were also overlaid onto the monthly NDDI maps to allow examination of the spatial co-occurrence of high NDDI values and active burning. For a more formal statistical treatment, each fire hotspot in the 2019–2024 record was assigned to the drought class of the pixel it fell in, based on the concurrent monthly NDDI map. This produced year-by-year distributions of hotspots across drought classes (Table 1). Finally, the NDDI-based approach was compared with traditional meteorological indices (notably SPI) to articulate how spatial drought mapping from satellite data can complement or exceed what is provided by point-based rainfall indicators.

3. Results and Discussion

3.1 NDDI Spatio-Temporal Patterns in Siak Regency

The spatial and temporal mapping of the NDDI drought index was conducted through automatic analysis using the Google Earth Engine (GEE) platform, with the main database being Sentinel-2 satellite imagery. The NDDI drought analysis was performed monthly across the administrative area of Siak Regency, Riau Province, Indonesia, from January 2019 to December 2024. Figure 3 presents an example of the analysis and mapping results of the monthly spatial distribution of NDDI in Siak Regency from January to December 2023. Yellow to brown colors represent higher NDDI values (drier conditions), while blue indicates lower values (wetter conditions). The maps show that peatland areas experiencing severe drought exhibit high NDDI values. Red points denote hotspots (active fire detections) indicating peat fires, which mostly occurred in areas with high NDDI (dry conditions). The figure illustrates the temporal dynamics of drought, which are consistent with the rainy and dry season conditions in the region. From January to May, NDDI values across most of the district remained below 0.01, indicating normal to humid conditions, consistent with the rainy season and the early transition period to the dry season. From June to September, drought conditions began to intensify, with NDDI values exceeding 0.25, particularly in areas adjacent to peat domes and plantation zones, shown in yellow to brown on the map.

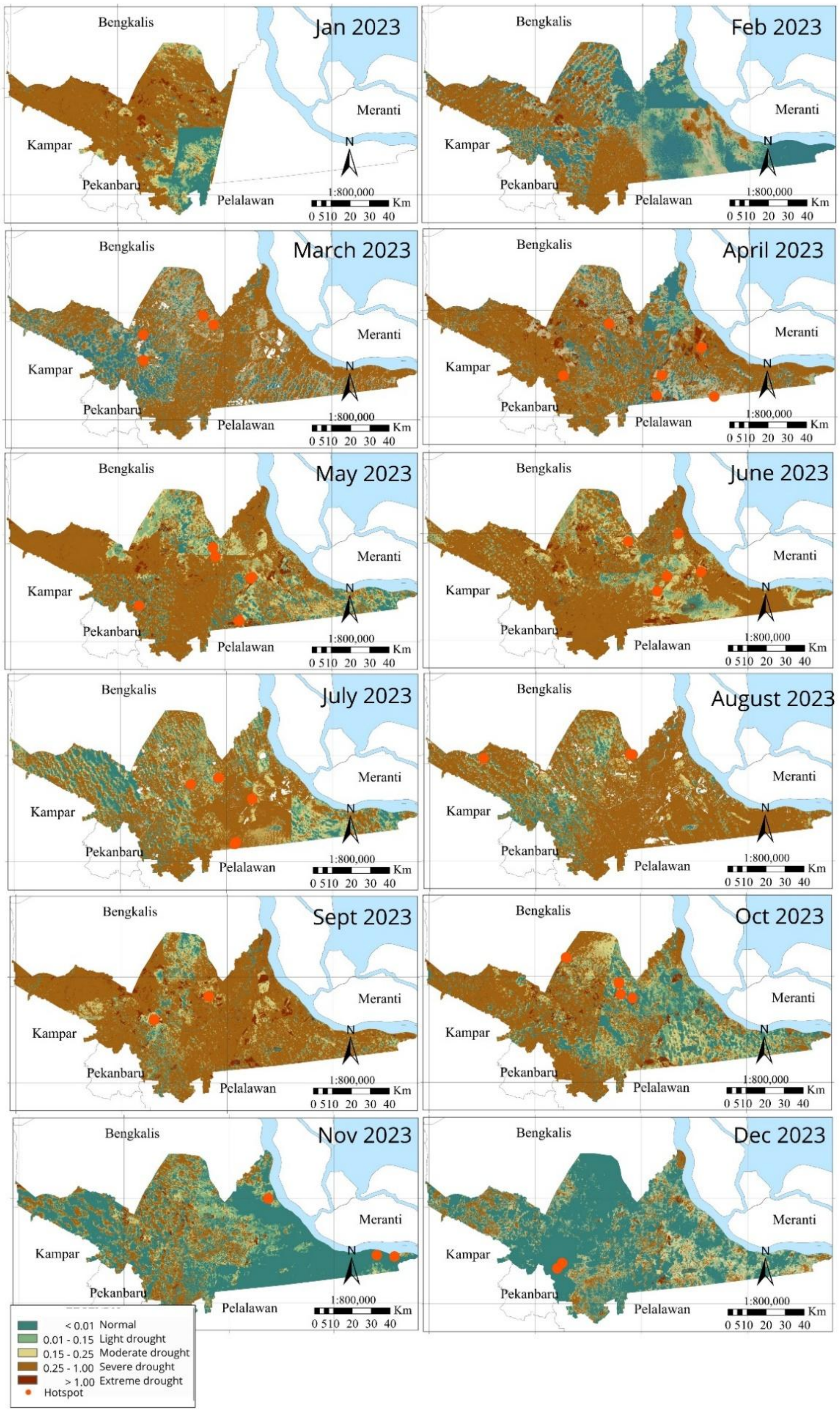


Figure 3. Monthly NDDI spatial distribution in Siak Regency from January to December 2023. Yellow to brown colors represent higher NDDI values (drier conditions), while blue indicates lower ones (wetter

conditions). The maps show that peatland areas experiencing severe dryness exhibit high NDDI values. Red points denote hotspots (active fire detections) indicating peat fires, which mostly occurred in areas with high NDDI (dry conditions).

The spatial distribution of drought levels follows several surface conditions that influence land drainage, such as land use and the degree of peatland degradation. In natural peat swamp forest areas, especially those near rivers and without drainage canals (southern and eastern Siak Regency), NDDI conditions can remain at low values (blue-green), consistent with higher natural groundwater levels and sufficient moisture. This clarifies that land drought assessments should be based not only on meteorological conditions, but also on the characteristics of the land surface, which vary in their hydrological response. This phenomenon can be effectively accommodated in the calculation of the drought index using the NDDI method.

Figure 4 shows the monthly temporal patterns of mean NDDI in Siak Regency from 2019 to 2024, together with the number of peatland fire hotspots. The figure indicates that peatland fires occurred every year during the study period, with varying severity; the most severe fires occurred in 2019, the highest number within the past six years. These fires typically occur during the dry season, when peatlands dry out and their organic material becomes combustible fuel. The NDDI results show substantial variability, ranging from near-normal conditions to severe drought, broadly following the alternation of rainy and dry seasons. Notably, several years exhibited a predominance of severe drought conditions, particularly 2019, 2020, 2021 and 2024. Monthly examination further confirms that severe fire events predominantly occurred under severe drought NDDI conditions. 2019 was the driest year on record, with an average of 10 months classified under severe drought and 2 months under moderate drought, which aligns with the fire occurrences observed throughout each month of severe drought. In contrast, the wettest conditions were recorded in 2022, followed by 2023, during which fire occurrences were notably rare.

Figure 5 shows the spatial distribution of NDDI and hotspots in Siak Regency in August 2019, which had the highest peatfire incidence in the study period. The maps show that peatland areas experiencing severe dryness exhibited high NDDI values (NDDI = 0.25-1.00). Red points denote hotspots (active fire detections), indicating peat fires, which mostly occurred in areas with high NDDI (dry conditions). The maps also indicate that severe and extreme dry conditions, indicated by brown and dark brown, predominantly occurred in the central and western parts of Siak Regency. Fire incidents during the study period were concentrated in these areas, aligning with the previous discussion. These areas are peatlands that have been utilised for oil palm plantations, accompanied by the construction of drainage canals. Meanwhile, the central-north and southeastern regions are predominantly colored green and blue, indicating low NDDI values (<0.15), with normal drought status. No peatland fires were observed in these areas in August 2019. They were identified as pristine peat swamp forest in the southeast and rice paddies in the central-northern areas, which retain moisture and are less prone to peat fires. This spatial pattern is consistent with the broader findings of the study, namely that peatland fires, particularly those in Siak Regency, mostly occur in locations suffering from severe drought. Therefore, the NDDI index map can be used as an indicator to assess fire-prone zones in heterogeneous peatland landscapes for various land uses, information that cannot be obtained by point-based meteorological indices alone.

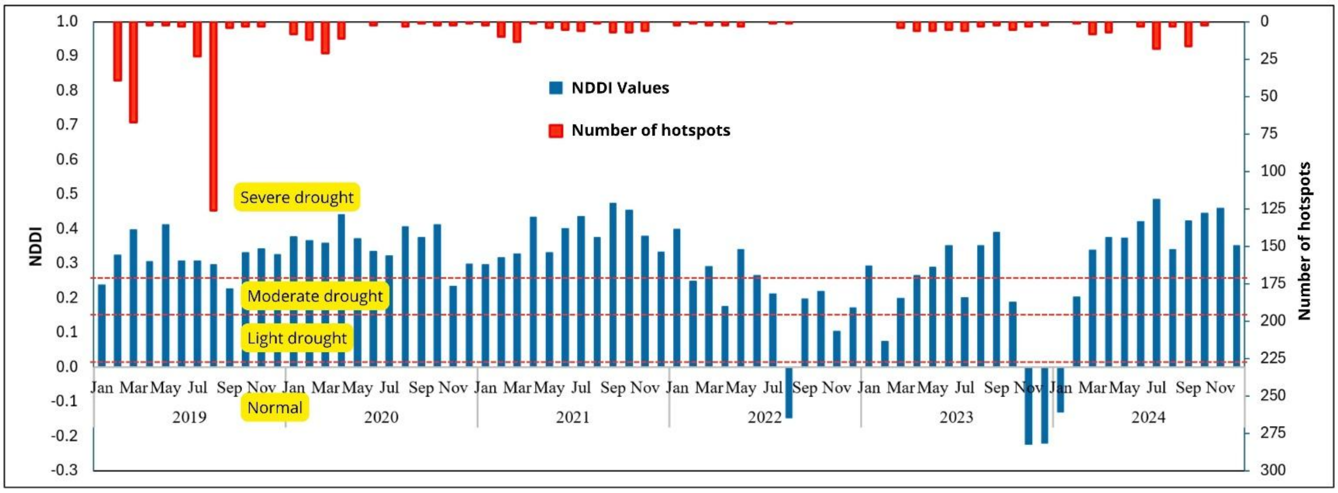
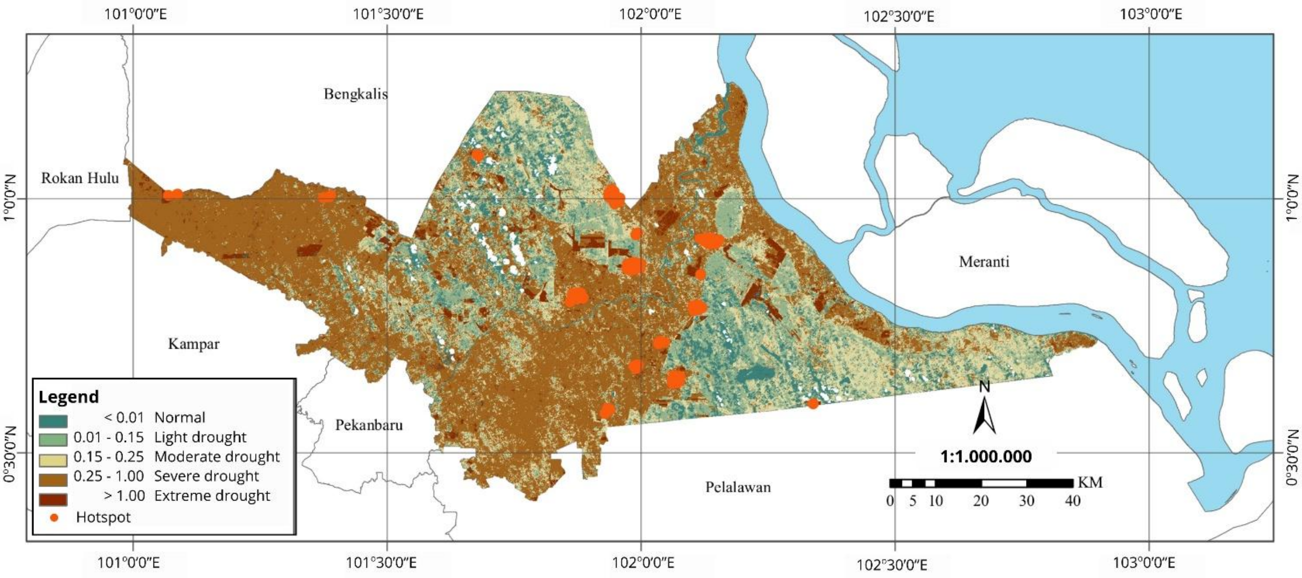


Figure 4. Monthly temporal patterns of mean NDDI in Siak Regency from 2019 to 2024 and the number of peatland fire hotspots. Peaks in NDDI (drought intensity) often precede or coincide with increases in fire occurrence, indicating that fires predominantly occur in peatlands with high (dry) NDDI values.



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3.2 NDDI and Peat Fire Occurrence

For a qualitative assessment of the relationship between drought severity and fire incidence, Table 1 breaks down annual hotspot detections by the NDDI drought class prevailing at the time and location of each detection. Based on the results summarised in the table, the discussion is outlined below. First, almost no fires were detected when peatland conditions were normal (not dry). However, the Normal moisture category made up less than 12% and 5% of all fire hotspots in 2023 and 2019 respectively, and was zero in most other years. This is plausibly because peatlands that are still wet and waterlogged are naturally resistant to fire; they simply cannot burn under moist conditions (Grosvenor *et al*., 2024). Second, the data clearly show that the majority of fire incidents occurred under Severe and Extreme drought conditions. From 2019 to 2024, approximately 78%, 90%, 92%, 100%, 86% and 98% of all hotspots in consecutive years were recorded within these two categories. A chi-square test confirmed that this concentration of fire within the drier classes is highly unlikely to have arisen by chance (chi-square = 96.1, df = 20, $p < 0.001$), which places the qualitative pattern above on a firm statistical footing.

2022, the wettest year in the study period (Figure 4), also consistently had the lowest number of fires, with 12 hotspots. However, all of these hotspots (100%) were recorded in the severe and extreme drought categories. This indicates that even in a wet year with relatively high rainfall, some areas may still experience drought depending on local hydrological and land surface conditions. This typically occurs in plantations with poor water management systems and high drainage rates due to extensive canal construction. This is one of the advantages of the NDDI drought mapping method compared to other conventional methods that rely solely on meteorological factors and do not account for land surface factors. The next wettest year, 2023, also consistently had the next lowest number of fires, with 42 hotspots. Almost all of these (96%) were also recorded in the extreme and severe drought category, as was the case in 2022.

Meanwhile, the dry years of 2019-2021 and 2024, with a high drought index (severe drought lasting more than 10 months per year), suffered a very high risk of peat fires, requiring significant attention paid to prevention efforts. In general, the multi-year pattern above, both in wet and dry years, provides evidence that drought classification using the NDDI method can effectively capture locations where peatland fire risk is concentrated (NDDI ≈ 0.25–0.30). This finding is generally consistent with previous studies conducted on Thai peatlands, which have a clear threshold for fire risk based on the drought index analyzed using the NDVI (NDVI = 0.6) (Khampeera *et al*., 2018). Overall, the hotspot analysis supports the conclusion that the NDDI is operationally useful as a spatial indicator, mapping where NDDI enters the severe drought range and identifying the peatlands most in need of preventive attention, although the index alone does not determine the timing of individual fires.

Table 1. Peatland fire incidents (2019–2024) by NDDI Drought Severity Category in Siak Regency. The values indicate the number of fire hotspots and (in parentheses) the percentage of the annual total. The concentration of fires in Severe and Extreme drought conditions in drier years (2019, 2023–2024) is evident.

Drought Index (NDDI)	2019 Hotspots (% of 2019 total)	2020 Hotspots (% of 2020 total)	2021 Hotspots (% of 2021 total)	2022 Hotspots (% of 2022 total)	2023 Hotspots (% of 2023 total)	2024 Hotspots (% of 2024 total)
Extreme drought	98 *(36%)*	24 *(38%)*	39 *(63%)*	11 *(92%)*	28 *(67%)*	49 *(84%)*
Severe drought	113 *(42%)*	33 *(52%)*	18 *(29%)*	1 *(8%)*	8 *(19%)*	8 *(14%)*
Moderate drought	39 *(14%)*	6 *(10%)*	3 *(5%)*	0 *(0%)*	1 *(2%)*	1 *(2%)*
Light drought	9 *(3%)*	0 *(0%)*	0 *(0%)*	0 *(0%)*	0 *(0%)*	0 *(0%)*
Normal	13 *(5%)*	0 *(0%)*	0 *(0%)*	0 *(0%)*	5 *(12%)*	0 *(0%)*
Total	272 *(100%)*	63 *(100%)*	60 *(100%)*	12 *(100%)*	42 *(100%)*	58 *(100%)*

The spatial concentration of fire in the dry classes is, however, only one side of the drought-fire relationship. When the association is examined temporally, by correlating the twelve monthly values of mean NDDI with the monthly hotspot counts within each year, the relationship is much weaker (Spearman rho ranging from -0.01 in 2019 to 0.52 in 2022, with a mean of 0.24). Only 2022 reached a moderate correlation, while 2019, the year of most intense burning, showed essentially none. The reason is evident in the monthly data: in 2019 the highest hotspot count occurred in August, yet that month ranked only tenth out of the twelve for mean NDDI, as the regency-mean index was diluted by areas that remained wet, even though fire was concentrated in the dry areas. This does not weaken the drought-fire link so much as locate it: NDDI is a strong indicator of where peatland is fire-prone, but a single monthly regency-mean value is a poor predictor of when fire will occur, because timing also depends on short-term rainfall and on human ignition, which the index does not include.

To confirm that the wet- and dry-year descriptions used above do not rest on the NDDI series itself, they were checked against an independent CHIRPS rainfall record and the official burnt-area record for the regency (Table 2). All three measures agree: 2019 was the driest year (1,901 mm annual rainfall) and the worst fire year (3,214 ha burned), while 2022 was the wettest (2,965 mm) and least affected (18 ha). Across the six years, annual rainfall and burnt area are strongly and significantly negatively correlated (Spearman rho = -0.94, p = 0.005): drier years clearly burn more. This confirms the meteorological control on between-year fire extent, and complements the NDDI results, which explain the within-year spatial distribution of fire.

Table 2. Annual and dry-season (June-September) rainfall for Siak Regency from CHIRPS, with the official annual burnt area and the peat fire hotspot counts used in this study, covering the period 2019-2024. The three measures agree in ranking 2019 as the most severe fire year and 2022 as the least.

Year	Annual rainfall (mm)	Jun-Sept rainfall (mm)	Burnt area (ha)	Hotspots (n)
2019	1,901	467	3,214	272
2020	2,411	697	562	63
2021	2,711	761	433	60
2022	2,965	855	18	12
2023	2,777	659	37.6	42
2024	2,536	625	380.1	58

Further independent support for this spatial reading comes from the historical burnt-area record (Figure 6), which maps the areas burnt in Siak between 2015 and 2020. Although this record largely predates the study period, this is in fact is what makes it informative: the areas that burned repeatedly are concentrated in the same peat-dome margins and river corridor that recorded the highest NDDI values during the 2019-2024 period. Fire in Siak is therefore not spatially random from year to year, but recurs in a persistent set of drained, degraded peatlands, which is the physical basis on which a surface drought index can map fire susceptibility.

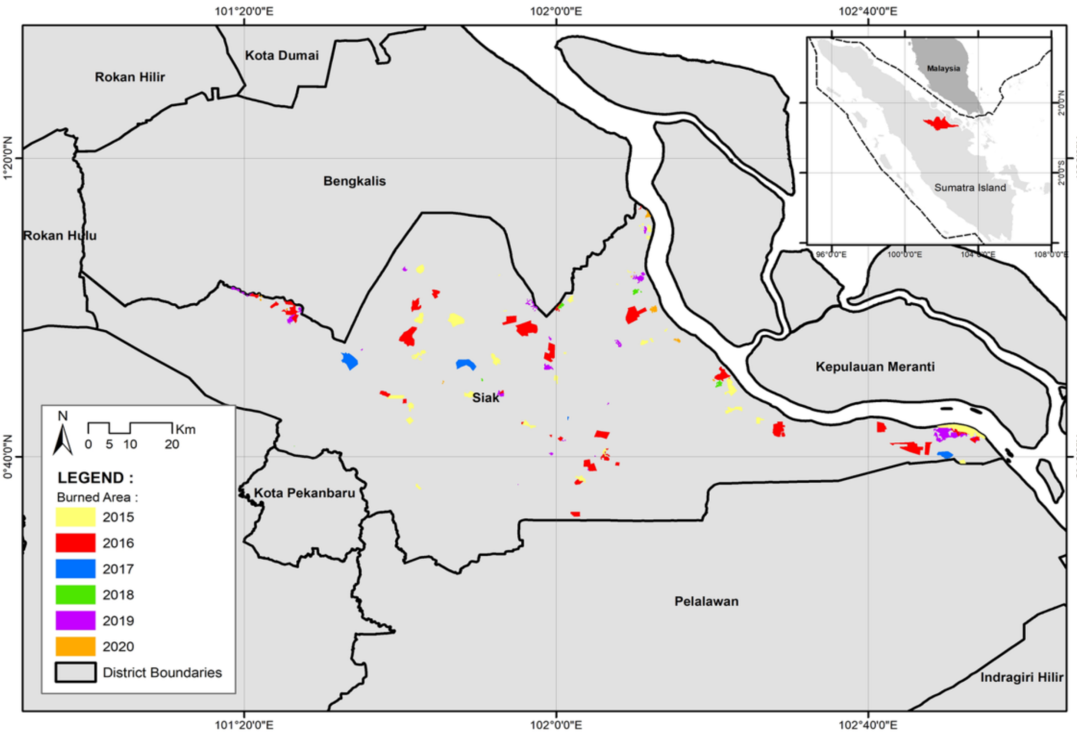

Figure 6. Areas burned in Siak Regency, 2015-2020, from official burnt-area data, color-coded by year. Repeated burning is concentrated in the central and western margins of the peat domes and along the Siak River, the same zones that recorded the highest NDDI and densest hotspots during the 2019-2024 period.

3.3. Discussion

The study provides new evidence that satellite-derived drought indices can significantly improve the monitoring of fire risk in tropical peatlands. By using the NDDI computed from high-resolution Sentinel-2 imagery on the GEE platform, the study has captured fine-grained patterns of peatland drought in Siak Regency and linked them to fire outcomes. The findings reinforce several important points in the context of peat fire management and scientific understanding.

The contrast between the strong spatial association and the weak temporal correlation is the most important study finding. Although NDDI locates fire-prone peatland reliably, a single monthly regency-mean does not by itself predict the month of burning, which is consistent with the wider understanding that drought sets the stage for fire, while the trigger is typically human (Purnomo *et al*., 2024; Mezbahuddin *et al*., 2023). The practical implication is that NDDI is best used as a spatial fire-susceptibility layer, updated monthly, and combined with short-term rainfall information and ignition-risk indicators to generate timing alerts, rather than being relied on as a stand-alone temporal predictor. Earlier ground-based analyses in Riau have reported a lead time between drought onset and fire using rainfall-based indices (Sukma & Sutikno, 2025; Irsyad *et al.,* 2025); establishing a comparable lead time for NDDI through a lagged predictive analysis is a clear direction for future work.

The second key finding relates to the accuracy of the NDDI calculation in depicting drought levels, which is not only based on meteorological data, as is typical for conventional drought index calculations, but also on surface characteristics and local hydrological conditions. This is because the NDDI method utilises high-resolution satellite imagery and analysis using machine learning available in Google Earth Engine (GEE). The use of Sentinel-2 multispectral satellite imagery with a spatial resolution of 10–20 m for drought detection significantly improves accuracy compared to the currently common MODIS. Therefore, this method can improve the sensitivity of drought mapping in complex peatland environments (Drusch *et al*., 2012; Román *et al*., 2024). Sentinel-2 has been recognised as providing reliable high-resolution satellite imagery for drought and vegetation monitoring as its spectral configuration and spatial detail enable the detection of more varied surface changes due to drought compared to previous medium-resolution satellite imagery (Varghese *et al*., 2021). Furthermore, multi-year dataset processing in GEE is efficient, scalable and user-friendly. On the GEE platform, NDVI, NDWI and NDDI indices can be rapidly calculated on entire image collections without relying on high-performance computing systems (Gorelick *et al*., 2017; Taminminia *et al*., 2020). This capability facilitates the practical operationalisation of drought monitoring workflows; even institutions with limited computing resources can implement near-real-time monitoring. Overall, the study demonstrates how combining free, high-resolution satellite data with cloud-based analytics can maximise advanced remote sensing applications to strengthen environmental monitoring and disaster risk reduction in peatlands.

When comparing NDDI with other drought calculation methods, such as the conventional meteorology-based SPI (Standardized Rainfall Index) and the KBDI (Keetch–Byram Drought Index), each method has its own advantages and disadvantages. The SPI method analyses drought based on insufficient rainfall in an area, without considering the local hydrological conditions of the land surface and land use. Similarly, the KBDI method is capable of detecting drought over a broad area, but is unable to account for local differences. A key parameter for assessing peatland damage and fire risk is groundwater depth, and rainfall-based drought index calculations do not measure this directly (Suharnoto *et al*., 2022). Vicente-Serrano *et al*. (2012) state that no single drought index calculation method is suitable for all situations. Each method is suited to specific conditions, characteristics and area coverage. However, our research found that the NDDI method is highly reliable for use in addressing peatland fires and their sustainable management. For better results in the future, it is recommended that the NDDI is used in conjunction with groundwater level measurements to understand their correlation. This combined approach will provide a more comprehensive picture of drought conditions, both at the surface and below ground (Mezbahuddin *et al*., 2023).

The findings have important implications for how peatlands should be managed. Over the six years of this study, peat areas that stayed wet (low NDDI) did not experience fires. This is not a coincidence; it reflects the well-known fact that when the underground water table remains high, peat is too moist to catch fire (Taufik *et al*., 2017). This confirms that rewetting drained peatlands is one of the most effective long-term strategies to prevent fires (Kiely *et al*., 2021; Sutikno *et al*., 2023; Pratama *et al*., 2020). Evidence from Riau Province supports this. After canal-blocking and rewetting programmes began in 2018, the number of extreme fire events dropped from seven (during the period 2015–2017, before rewetting) to four (during the period 2018–2021, after rewetting), as reported by Taufik *et al* (2023). This shows that restoring peatland hydrology can meaningfully reduce fire occurrence. The drought maps produced for the study can also help guide where restoration efforts should be focused. Peat dome areas in Siak that consistently show high NDDI values during dry seasons are the locations that would benefit most from canal blocking and rewetting. Meanwhile, pristine peat swamp forests that remain naturally moist should continue to be protected from land conversion and canalisation, as such forests already function as natural barriers against fires.

On a practical level, NDDI monitoring can be directly used to support preparedness for the threat of peat fires. For example, when the threshold is approaching the transition from moderate to severe drought, with an NDDI approaching 0.25, local authorities can declare a peat fire risk in their area. This announcement is intended to increase all relevant stakeholders' awareness of peat fires. Operational measures that can be implemented in this situation include increasing water retention in drainage canals by blocking them; cloud seeding as a weather modification strategy to accelerate rainfall; social approaches to encourage caution in the use of fire on land; and fire patrols as a rapid response in the event of a peat fire (Sandhyavitri *et al*., 2018; Sutikno, *et al*., 2020). Community involvement is key to peat fire prevention efforts, as it is they who are likely to be in fire-prone areas on a daily basis. In general, fire-prone areas already have MPA (Masyarakat Peduli Api, Community Fire Awareness Groups) responsible for extinguishing peat fires. Monthly NDDI drought updates can be disseminated to communities, including MPAs, so that when conditions begin to pose a peat fire risk, they can take preventative measures. Communication channels using social media can expedite the distribution of NDDI drought map updates in their respective areas. This system will bring scientific monitoring directly to communities on the ground, combining official government responses from above with active community participation from below (Purnomo *et al*., 2024).

The study has several limitations that should be considered when interpreting the results. First, NDDI is a surface-based index, meaning it only measures moisture in the vegetation and the top layer of the soil. It cannot detect how dry the deeper peat layers are beneath the surface. This is a concern because deep peat can still be dangerously dry even when the surface vegetation looks green and healthy (Burdun *et al*., 2023). To partially address this, we cross-checked our results with burn scar data and confirmed that most fire-affected areas did show high NDDI values in the weeks before fires occurred. Second, cloud cover is a common problem in tropical regions. Despite using monthly composite images, some areas still had insufficient cloud-free observations, particularly during the rainy season, leaving gaps in the NDDI record. One possible solution for future studies is to combine optical satellite data with synthetic aperture radar (SAR) imagery, which can see through clouds and would help fill these gaps (Suseno *et al*., 2025). Third, the fire hotspot data from FIRMS (MODIS and VIIRS sensors) may not capture all fires, especially low-intensity smouldering peat fires that produce little heat or are hidden by smoke haze. Previous studies have shown that MODIS misses a significant number of peat fires that are only detected by higher-resolution sensors (Sirin & Medvedeva, 2022; Atwood *et al*., 2016). This situation can lead to bias or inaccuracy in the analysis. Therefore, future research should utilise fire data not only in the form of hotspots, but also high-resolution burnt area data processed from Sentinel-2 or SAR to improve accuracy (Arjasakusuma *et al*., 2022).

Finally, although the research focuses on Siak Regency, the same methodology can be applied to other tropical peatland areas in Indonesia, such as Kalimantan and Papua, which have similar peat fire characteristics. Expanding this approach nationally could support the development of a standardised peatland fire early warning system across Indonesia.

4. Conclusion

The study has analysed drought by calculating the NDDI index using Sentinel-2 multispectral imagery on the Google Earth Engine platform and applied it to tropical peat fires in Siak Regency, Riau Province, Indonesia. The results show a strong spatial association between the NDDI drought index and peatland fire occurrence: in the six years from 2019 to 2024, an average of 91% of hotspots (85% pooled across all 507 detections) were located in areas with an NDDI greater than 0.25, categorised as severe and extreme drought, and a chi-square test confirmed that this concentration was highly significant ($p < 0.001$). By contast, the month-to-month temporal correlation was weak (mean rho = 0.24), showing that the surface drought signal alone does not determine the timing of fire within a season; an independent CHIRPS rainfall record confirmed the wet- and dry-year ranking and yielded a significant negative correlation between annual rainfall and burnt area (rho = -0.94, $p = 0.005$). Our research demonstrates that the NDDI method can accurately depict the drought conditions of an area, relying not only on meteorological conditions, as with other conventional methods, but also on ground surface conditions, which is the source of its spatial strength.

From a management perspective, the findings suggest that NDDI monitoring during the dry season could support early-warning alerts; pre-positioning of firefighting resources; and targeted water-management interventions before fires start. The spatial resolution of 10–20 m of the Sentinel-2 imagery, combined with GEE's efficient processing of multi-year archives, makes this approach scalable and reproducible without expensive local computing infrastructure. Policymakers can use recurrent drought-hotspot maps to prioritise peatland rewetting, canal-blocking and conservation investment in the areas most prone to drying. Ultimately, the value of this work lies not simply in what it shows about Siak specifically, but in establishing a transferable methodology for proactive, satellite-driven peat fire risk management applicable across Indonesia's extensive peatland regions. We recommend wider adoption and refinement of this approach, including integration with subsurface hydrological monitoring and community-based observation networks, as next steps toward the fuller exploitation of remote sensing for peatland disaster risk reduction.

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Author Contributions

Conceptualization: Sutikno, S., Wy, I.H., **methodology**: Sutikno, S., Wy, I.H., **investigation**: Wy, I.H., Saily, R., **writing—original draft preparation**: Sutikno, S., Darfia, N.E., Wy, I.H., **writing—review and editing**: Yamamoto, K., Sutikno, S., Saily, R., Silviana, S.H., **visualization**: Wy, I.H., Sutikno, S., All authors have read and agreed to the published version of the manuscript.

Conflict of interest

All authors declare that they have no conflicts of interest.

Data availability

Data is available upon request.

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