

Open-data remote sensing framework for peat hydrological unit condition scoring in South Sumatra Peatlands (2018-2024)

Muaffan Alfaiz Wisaksono^{1*)}, Abdhullah Syawalbhi Leo²

¹Master's Programme in Precision Agriculture, Faculty of Agribusiness and Commerce, Lincoln University, Ellesmere Junction Road, Lincoln 7647, Lincoln, New Zealand

²School of Geography, Earth and Atmospheric Sciences, University of Melbourne, Parkville, Victoria 3010, Australia

^{*)}Email address: muaffan.wisaksono@lincolnuni.ac.nz

(Received: 27 April 2026, Revision accepted: 11 September 2026)

Citation: Wisaksono, M. A., & Leo, A. S. (2026). Open-data remote sensing framework for peat hydrological unit condition scoring in South Sumatra peatlands (2018-2024). *Jurnal Lahan Suboptimal : Journal of Suboptimal Lands*. 15 (2): 106–119. <https://doi.org/10.36706/JLSO.15.2.2026.818>

ABSTRACT

Tropical peatland degradation remains a critical environmental challenge in Southeast Asia, yet operational monitoring frameworks that align with governance boundaries remain limited. This study aimed to develop an open-data remote sensing framework for assessing peatland condition at the Peat Hydrological Unit (Kesatuan Hidrologis Gambut, KHG) scale in South Sumatra, Indonesia. Using Google Earth Engine, four satellite-derived indicators were extracted annually for 12 KHGs over seven years from 2018 to 2024: Normalized Difference Water Index from MODIS MOD09A1, Enhanced Vegetation Index from MODIS MOD13Q1, fire frequency from NASA FIRMS, and surface water extent from the JRC Global Surface Water dataset. The indicators were normalized and integrated into a weighted composite score using weights of 30% for NDWI, 25% for EVI, 30% for inverse fire frequency, and 15% for surface water extent. In 2024, seven KHGs were classified as At Risk and five as Intact/Recovering, with scores ranging from 46.5 to 76.9. Six KHGs declined between 2018 and 2024, while five improved. El Niño years reduced health scores by an average of 11.3 points, and cropland conversion was the strongest land-cover predictor of lower scores ($r=-0.52$). Weight sensitivity analysis showed that seven of twelve KHG classifications remained stable across five weighting scenarios. The framework was reproducible, governance-aligned, and suitable as a screening tool for peatland restoration prioritisation.

keywords: google earth engine, multi-criteria assessment, peat hydrological unit, peatland monitoring, remote sensing

INTRODUCTION

Tropical peatlands store approximately 89 Gt of carbon globally (United Nations Environment Programme, 2022; Omar et al., 2022). In Indonesia, peatlands are widely distributed across major lowland regions, including Sumatra and Kalimantan (Omar et al., 2022). When degraded through drainage, fire, or land-use conversion, these carbon-rich ecosystems become major sources of greenhouse gas emissions and transboundary haze pollution, as demonstrated during the catastrophic fire events of 2015 and 2019 (Crippa et al., 2016; Tacconi, 2016). South Sumatra Province, with approximately 1.7 million hectares of peatland distributed across 34 Peat Hydrological Units (Kesatuan Hidrologis

Gambut, KHG), represents one of Indonesia's most fire-prone and ecologically vulnerable peatland regions (UNDRR, 2024).

The Indonesian government has established a regulatory framework for peatland protection and restoration. Government Regulation No. 57/2016 mandates maintaining peat water tables within 40 cm of the surface, while Ministerial Decree SK.129/2017 formally delineates 865 KHG boundaries nationwide as the operational spatial unit for peatland management (Ministry of Environment and Forestry of the Republic of Indonesia, 2017). The Peatland and Mangrove Restoration Agency (BRGM, formerly BRG) has been tasked with restoring 2.67 million hectares of degraded peatland, including 656,884 hectares in South Sumatra (Peatland and Mangrove

Restoration Agency or BRGM, 2021). Despite this institutional framework, systematic condition monitoring at KHG scale remains limited, with most assessments relying on spatially sparse field observations or satellite analyses conducted at administrative rather than hydrological boundaries.

Remote sensing has been widely applied to peatland monitoring in Indonesia, including vegetation indices for canopy condition (Miettinen et al., 2016), fire hotspot data for burning intensity and recurrence (Vetrita & Cochrane, 2020), radar backscatter for soil moisture dynamics (Lees et al., 2018), and optical water indices for surface inundation patterns (Dadap et al., 2019). However, many studies adopt pixel-level or administrative-boundary aggregation approaches, neither of which directly corresponds to the KHG unit that governs peatland management decisions. This mismatch between analytical and governance units limits the direct applicability of remote sensing outputs to restoration planning and regulatory compliance monitoring.

Several frameworks have been proposed for multi-indicator peatland assessment. Cahyono et al. (2022) developed a scoring system integrating hydrological, topographical, and remote-sensing variables for peatland restoration prioritisation, while demonstrating the relationship between drainage depth and carbon emissions in Sumatran peatlands. Minasny et al. (2019) further highlighted the importance of digital mapping approaches for peatland assessment. Yet many existing approaches require proprietary data, field measurements, or specialised computational environments, creating barriers to routine operational deployment by provincial environmental agencies with limited technical capacity and budgets.

This study addresses these gaps by presenting a fully open-data, reproducible framework for peat condition scoring at KHG scale. The framework integrates four complementary satellite-derived indicators — water content (NDWI), vegetation health (EVI), fire pressure (FIRMS), and surface water extent (JRC GSW) — into a weighted composite score that classifies each KHG along a degradation–recovery continuum. The workflow runs in Google Earth Engine and Python, uses

freely accessible satellite archives from 2018 to 2024, and produces outputs aligned with the government's KHG governance boundaries. By incorporating weight sensitivity analysis, land cover composition, El Niño impact quantification, and per-unit driver decomposition, the framework provides condition maps and interpretive context for management prioritisation.

The objectives of this research was to develop and apply a multi-indicator remote sensing scoring framework for peat condition assessment at KHG scale, to characterise spatial and temporal peatland health patterns across South Sumatra from 2018 to 2024, to identify dominant degradation and recovery drivers at individual KHG level, and to evaluate framework robustness through weight sensitivity analysis.

MATERIALS AND METHODS

Study Area

South Sumatra Province (1.5°S–4.5°S, 103°E–106°E) was located in the southeastern part of Sumatra Island, Indonesia. The province forms part of the lowland tropical peatland region of insular Southeast Asia, where peatlands store globally significant carbon stocks and were concentrated across the coastal lowlands of Sumatra, Borneo, and Peninsular Malaysia (Miettinen et al., 2016; United Nations Office for Disaster Risk Reduction, 2024; Omar et al., 2022). South Sumatra contains approximately 1.7 million hectares of peatland, making it one of the major peatland provinces in Sumatra after Riau (KLHK, 2017; Omar et al., 2022).

Based on the official KHG boundary delineation under Ministerial Decree SK.129/MENLHK/SETJEN/PKL.0/2/2017, the study area encompasses 12 distinct Peat Hydrological Units (KHG) ranging in size from 15.8 km² (KHG.16.07.08) to 874.7 km² (KHG.16.02.08). The use of KHG boundaries was consistent with Indonesia's peatland governance framework, which treats ecosystem and hydrological boundaries as the operational basis for peatland protection, restoration, and management (KLHK, 2017; Rossita et al., 2021).

These KHGs span diverse landscape conditions, from relatively intact forested peatlands in interior and less accessible areas to

heavily converted agricultural and plantation-dominated peatlands in lowland areas closer to rivers, settlements, and transport infrastructure. This gradient was consistent with broader peatland-conversion patterns in Sumatra, where peat swamp forests have declined substantially since 1990 and managed land-cover types, including industrial plantations and smallholder agricultural areas, have expanded across peatland landscapes (Miettinen et al., 2016). South Sumatra had a tropical monsoon climate with a marked dry season, during which peatland water levels decline, and fire risk increases. Previous studies in South Sumatra have shown that peat fires were strongly associated with dry-season rainfall deficits, groundwater-level decline, and climate anomalies related to El Niño and the Indian Ocean Dipole (Putra et al., 2019; Nurhayati et al., 2021; Irfan et al., 2024). In peat-dominated districts such as Ogan Komering Ilir, annual rainfall was generally high, but fire occurrence peaks during the dry-season months, especially September and October, when rainfall was lowest and peat surfaces become more combustible (Nurhayati et al., 2021; Irfan et al., 2024). The spatial distribution of the 12 KHGs and their 2024 condition scores were presented in Figure 1.

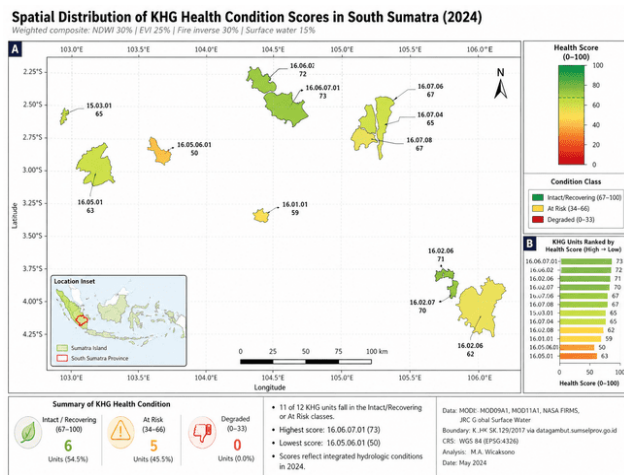


Figure 1. Spatial distribution of Peat Hydrological Unit (KHG) health condition scores in South Sumatra, 2024. Scores were derived from a weighted composite of NDWI (30%), EVI (25%), fire frequency inverse (30%), and surface water extent (15%). Classification thresholds: Degraded (0–33), At Risk (34–66), Intact/Recovering (67–100).

Data Sources

This study used four satellite-derived datasets and one land cover product, all accessed through Google Earth Engine or direct download from

open repositories (Table 1). The exclusive use of open-access data sources was a deliberate design choice to ensure full reproducibility of the framework.

Table 1. Satellite datasets and boundary data used in this study

Dataset	Source	Resolution	Temporal	Period	Indicator Derived
MOD09A1	MODIS/061	500 m	8-day	2018–2024	NDWI (peat water content)
MOD13Q1	MODIS/061	250 m	16-day	2018–2024	EVI (vegetation health)
FIRMS	NASA LANCE	1 km	Daily	2018–2024	Fire Pixel Frequency
JRC GSW v1.4	JRC/EC	30 m	Monthly	2018–2024	Surface Water Extent
WorldCover	ESA	10 m	Annual	2021	Land Cover Composition
KHG boundary	KLHK	1:50,000	—	2017	Analytical Spatial Unit

Analytical Framework Data Extraction Pipeline

All satellite data processing was conducted in Google Earth Engine, enabling reproducible, cloud-based analysis of long-term satellite archives (Gorelick et al., 2017). For each KHG polygon, annual composites were generated by aggregating valid observations within each calendar year from 2018 to 2024. NDWI was derived from MODIS MOD09A1 surface reflectance using NIR band 2 and SWIR band 6, following the NIR–SWIR formulation proposed for vegetation and surface moisture detection (Burdun et al., 2023; Koupaei-Abyazani et al., 2024; Vermote, 2021). In this study, NDWI was interpreted as a KHG-scale moisture proxy rather than a direct water-table measurement.

Vegetation condition was represented using EVI from MODIS MOD13Q1, a 250 m, 16-day vegetation index product designed for regional vegetation monitoring (Didan, 2021). EVI values were rescaled using the MODIS scale factor of 0.0001. Fire frequency was calculated by counting annual active fire detections within each KHG using NASA FIRMS data. Active fire products were widely used for regional fire monitoring, but they represent thermal detections rather than complete burned-area estimates (Giglio et al., 2016). Therefore, fire frequency was treated as a proxy for fire pressure.

Surface-water context was derived from the JRC Global Surface Water dataset, which maps global surface-water dynamics from Landsat imagery at 30 m resolution (Pekel et al., 2016). Because the JRC monthly history product currently provides observations up to 2021, this variable was treated as a historical surface-water context layer rather than a fully dynamic annual indicator for 2022–2024. Pixels classified as water were summarised within each KHG and converted into fractional surface-water area to represent long-term surface-water presence and hydrological limitation. Annual moisture dynamics across the full 2018–2024 period were therefore interpreted primarily through the MODIS-derived NDWI indicator. Where KHG boundaries contained multiple fragments, annual statistics were calculated per fragment and merged using area-weighted averaging.

Composite Scoring Framework

Each indicator was normalised to a 0–100 scale using min–max normalisation to allow aggregation of variables with different units and ranges, following common composite-indicator practice (Greco et al., 2019). Fire frequency was inverted before normalization so that higher values consistently represented better condition. The composite health score was calculated as:

$$\text{Health Score} = (NDWI_{norm} \times 0.30) + (EVI_{norm} \times 0.25) + (Fire_{inv,norm} \times 0.30) + (Water_{norm} \times 0.15)$$

The weighting structure follows GIS-based multi-criteria decision analysis principles, where standardised spatial indicators were weighted and combined for environmental prioritisation (Greco et al., 2019). Higher weights were assigned to moisture condition and fire pressure because hydrological disturbance and fire were major drivers of tropical peatland degradation, subsidence, and carbon loss (Anshari et al., 2021; Koupaei-Abyazani et al., 2024; Dadap et al., 2019; Vetruta & Cochrane, 2020; Irfan et al., 2024). Vegetation health was included as an integrative ecological response, while surface water extent was treated as a supplementary rewetting signal. KHGs were classified into three screening categories: Degraded (0–33), At Risk (34–66), and Intact/Recovering (67–100). These classes

were used for management prioritization rather than as field-validated ecological thresholds.

Enhancement Analyses

We conducted a weight sensitivity analysis by comparing the baseline weighting with four alternative scenarios: fire-dominant, vegetation-dominant, water-dominant, and equal-weight scenarios. This was used to evaluate whether KHG classifications were robust to weighting assumptions, which was recommended in composite-indicator assessment (Greco et al., 2019). Land-cover composition was calculated from ESA WorldCover 2021, a 10 m global land-cover product derived from Sentinel-1 and Sentinel-2 data (Zanaga et al., 2022). WorldCover classes were grouped into forest and mangrove, cropland and plantation, degraded open land, and wetland and water. Pearson correlation coefficients were then used to explore associations between land-cover proportions and health scores.

We assessed El Niño impact by comparing mean KHG scores during El Niño years (2019 and 2023) with non-El Niño years. This comparison was used because peatland fire risk increases when drought, low rainfall, and groundwater decline coincide during climate anomalies (Dadap et al., 2019; Vetruta & Cochrane, 2020; Irfan et al., 2024; Putra et al., 2019). Finally, driver decomposition was performed by calculating the weighted contribution of each indicator to the 2024 score and identifying the lowest normalized indicator as the limiting factor. This was interpreted as a diagnostic screening tool, not as formal causal attribution.

RESULTS

Spatial Distribution of Peat Condition (2024)

The 2024 condition assessment classified seven of twelve KHGs as At Risk (scores 46.5–64.8) and five as Intact/Recovering (scores 67.1–76.9) (Figure 1). No KHG was classified as Degraded under the baseline weighting. The lowest-scoring unit, KHG.16.07.08 (score 46.5), was a small (15.8 km²) unit characterised by low NDWI and the highest proportion of cropland conversion (67%). The highest-scoring unit, KHG.16.02.06 (score 76.9), was a medium-sized (87.1 km²) unit that retains 71% forest cover with minimal

agricultural encroachment. Figure 2 shows the ranked distribution of condition scores across all KHGs and highlights the clustering of At-Risk units within a narrow score band of 46–65.

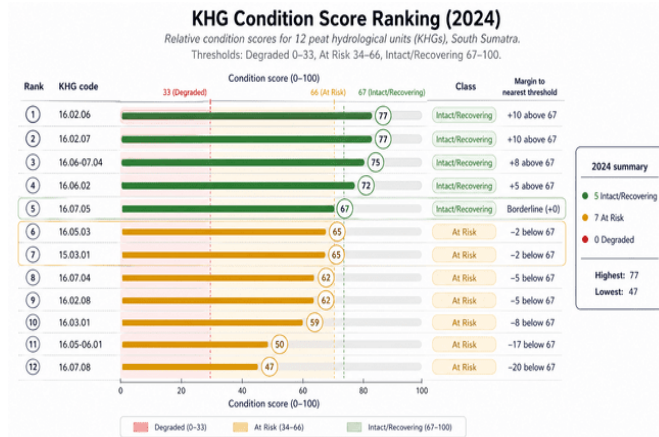


Figure 2. Ranked health condition scores for 12 KHGs in South Sumatra, 2024. Horizontal bars were coloured by condition class: red (Degraded, 0–33), orange (At Risk, 34–66), green (Intact/Recovering, 67–100). Dashed lines indicate classification thresholds.

A clear spatial gradient was observed, with eastern lowland KHGs (closer to the coast and major river systems) generally scoring lower than western and interior KHGs. This pattern aligns with the well-documented east–west gradient of peatland conversion in Sumatra, where lowland peatlands closer to transportation infrastructure have experienced more extensive drainage and agricultural development (Miettinen et al., 2016; Omar et al., 2022).

Temporal Trends (2018–2024)

Figure 3 presents the multi-year evolution of conditions across all seven assessment years, showing the spatial distribution of health scores for each year from 2018 to 2024 in a small-multiples format. The visual progression reveals that while some KHGs have maintained relatively stable conditions, others have undergone substantial changes in both directions.

Figure 4 plots the annual score trajectories for all 12 KHGs, revealing the divergent pattern more explicitly. Six KHGs exhibited declining health scores between 2018. To examine the specific indicator trends underlying the composite score changes, Figure 6 presents the NDWI and EVI trajectories for the three most-improved and three most-declined KHGs. The improved units show

increasing NDWI (wetter conditions) and stable or increasing EVI (vegetation recovery), while declining units exhibit the opposite pattern: decreasing water content and vegetation deterioration. In 2024, KHG.16.05-06.01 showed the largest decline (−10.2 points). Conversely, five KHGs improved, with KHG.16.02.07 showing the most substantial recovery (+25.8 points). One unit (KHG.16.07.05) remained stable (−1.3 points). The sharp dips visible in 2019 and 2023 across most trajectories correspond to El Niño events, which were analysed separately in Section 4.3.

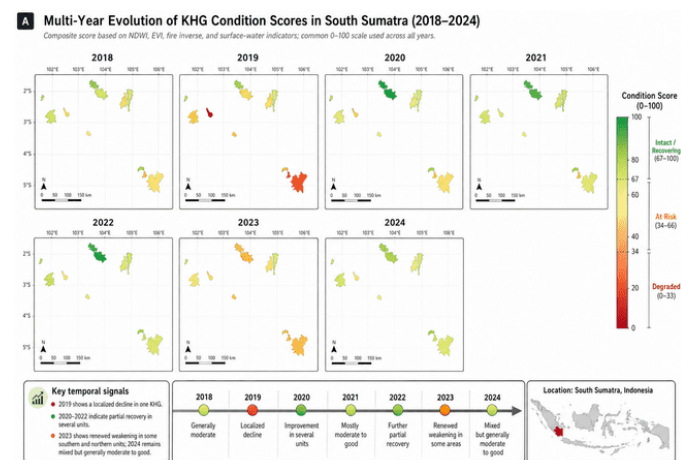


Figure 3. Multi-year evolution of KHG health scores in South Sumatra (2018–2024). Each panel shows the spatial distribution of composite health scores for one year. Color scale: red (low score) to green (high score). The panels illustrate temporal variation driven by both chronic trends and inter-annual climate fluctuations.

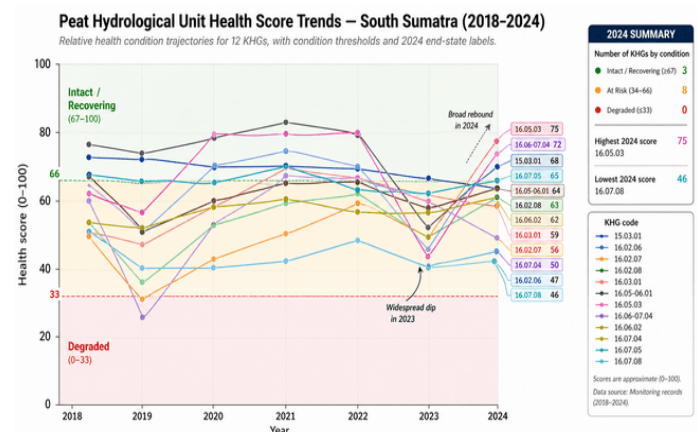


Figure 4. Health score trajectories for all 12 KHGs in South Sumatra (2018–2024). Background shading indicates condition class thresholds. Sharp score dips in 2019 and 2023 correspond to El Niño events.

The spatial distribution of score changes between 2018 and 2024 was mapped in Figure 5, where green indicates improving and red indicates declining KHGs. The map reveals that improving

units were distributed across different parts of the province, suggesting that the recovery signal was not confined to a single geographic cluster but may reflect spatially distributed restoration interventions.

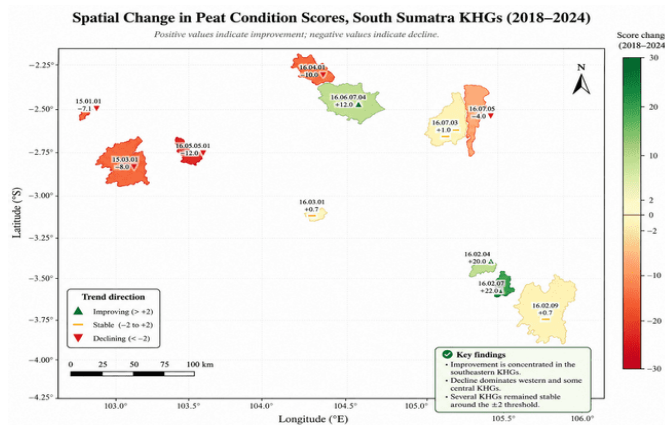


Figure 5. Spatial distribution of health score change between 2018 and 2024. Green indicates improvement, yellow indicates stability, and red indicates decline. Arrow symbols and numeric labels show the direction and magnitude of change for each KHG.

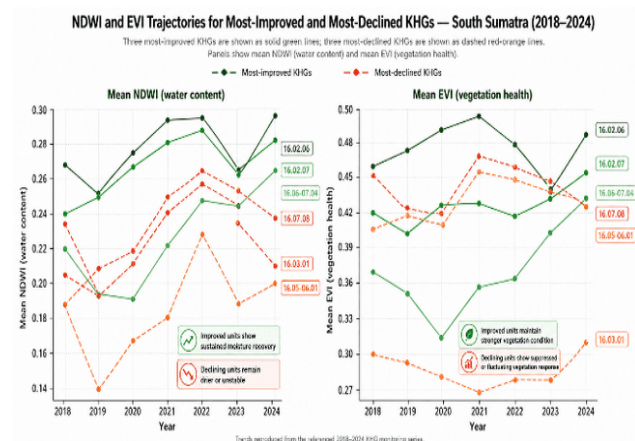


Figure 6. NDWI (left) and EVI (right) trends for the three most-improved (solid green lines) and three most-declined (dashed red lines) KHGs, 2018–2024. Improving units show increasing water content and stable vegetation, while declining units show drying and vegetation loss.

El Niño Impact and Fire Dynamics

El Niño years (2019 and 2023) produced a substantial and consistent reduction in peatland health across the study area. Figure 7 presents a paired comparison of mean health scores during El Niño years versus normal years for each KHG (left panel), together with the magnitude of the score drop (right panel). The average score reduction across all KHGs was 11.3 points, but the impact varied substantially among units. KHG.16.06-07.04 experienced the largest drop (−24.9 points)

despite maintaining 77% forest cover, indicating that even well-forested peatlands were vulnerable to severe ENSO-driven drying and fire. In contrast, KHG.15.03.01 was essentially unaffected (+0.3 points), which may be attributed to its near-total forest cover (98%) and presumably higher water retention capacity.

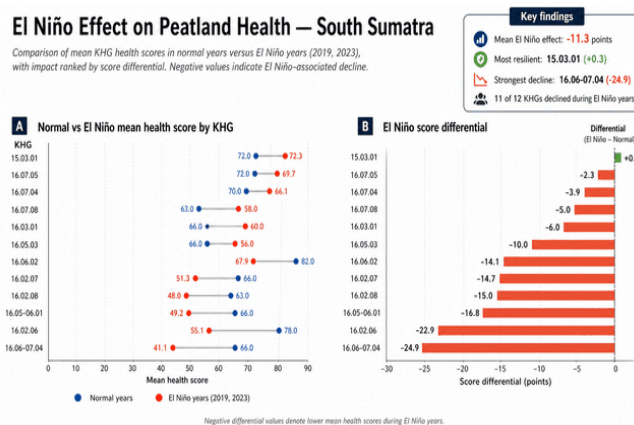


Figure 7. El Niño impact on peatland health. Left panel: paired mean health scores during normal years (blue) and El Niño years (red) for each KHG. Right panel: score differential, where negative values indicate El Niño-driven decline. KHGs sorted by impact magnitude.

The temporal distribution of fire activity across KHGs was shown in Figure 8. The fire frequency heatmap reveals pronounced spikes in 2019 and 2023, consistent with the El Niño-driven fire seasons documented across Indonesia during these years (UNDRR, 2024). KHG.16.06-07.04 and KHG.16.05-06.01 consistently recorded the highest fire pixel counts, while KHG.15.03.01 and KHG.16.06.02 had minimal fire activity across all years.

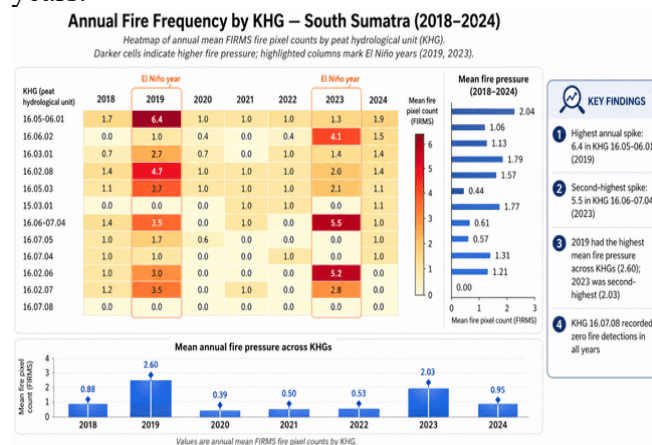


Figure 8. Annual fire frequency heatmap by KHG (2018–2024). Cell values represent mean fire pixel counts per year. Darker colours indicate higher fire pressure. Spikes in 2019 and 2023 correspond to El Niño events.

The cumulative spatial distribution of fire density across the seven-year study period was shown in Figure 9. Fire density (fires per km²) normalises the raw fire count by KHG area, revealing that smaller units with moderate fire counts can have high fire density. KHG.16.05-06.01, located in the central peatland belt, shows the highest fire density per unit area.

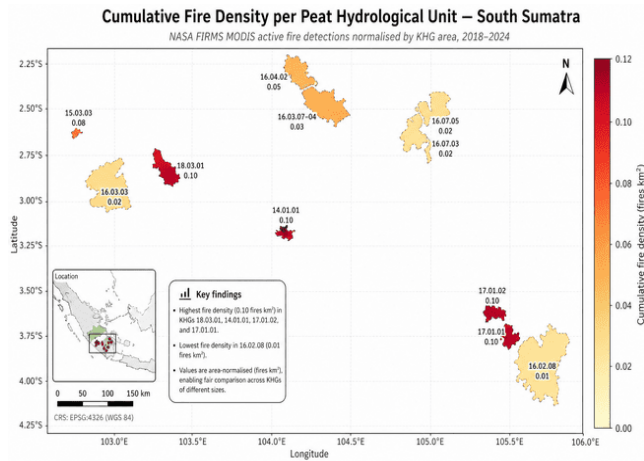


Figure 9. Cumulative fire density (fires per km², 2018–2024) per KHG. Fire density normalises total fire pixel count by KHG area, allowing comparison across units of different sizes.

Land Cover Drivers of Degradation

Land cover analysis using ESA WorldCover 2021 revealed marked differences in composition across KHGs. Figure 10 presented the proportional land cover breakdown for each KHG, sorted by forest cover. The composition ranges from KHG.15.03.01 (98% forest, effectively intact) to KHG.16.07.08 (12% forest, 67% cropland, heavily converted). Intermediate units show varying mixes of forest, open degraded land, and agricultural conversion.

The relationship between land cover and health score was examined in Figure 11 through three scatter plots. Cropland and plantation cover showed the strongest negative correlation with health score ($r = -0.52$, $p < 0.05$), while forest cover showed a positive but weaker association ($r = 0.37$). The relationship between open degraded land and health score was weak and non-significant ($r = 0.19$), suggesting that transitional land cover types encompass both degrading and naturally recovering states that do not consistently predict condition. These correlations indicate that agricultural conversion was a more reliable

indicator of peat degradation than the presence of open or disturbed vegetation.

Land Cover Composition by KHG — South Sumatra (ESA WorldCover 2021)

KHGs ranked by forest and mangrove cover. Shares are aggregated from ESA WorldCover 2021 (10 m resolution).

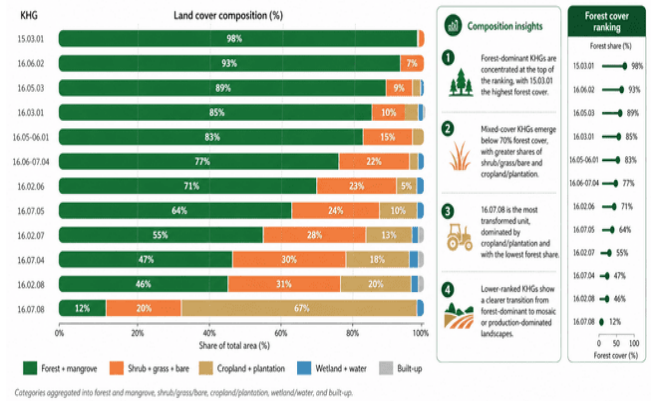


Figure 10. Land cover composition per KHG based on ESA WorldCover 2021 (10 m resolution). Categories were aggregated into forest and mangrove (green), shrub, grass, and bare (orange), cropland and plantation (tan), wetland and water (blue), and built-up (grey). KHGs sorted by forest cover percentage.

Land Cover vs Peat Health Score — What's Driving Degradation?

South Sumatra Peat Hydrological Units (12 KHGs) — 2024

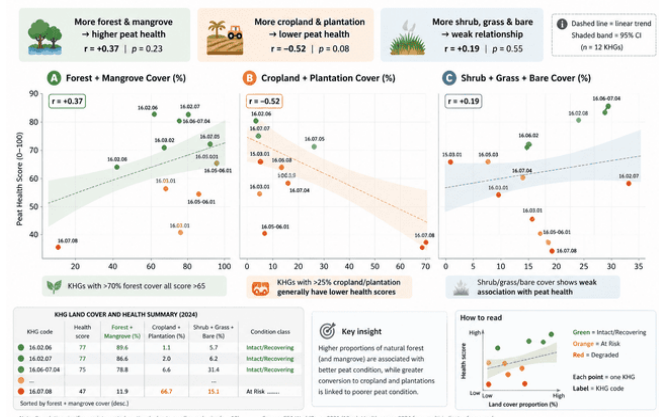


Figure 11. Scatter plots of land cover proportions versus health score for 12 KHGs: forest and mangrove (left, $r = 0.37$), cropland and plantation (centre, $r = -0.52$), and shrub, grass, and bare (right, $r = 0.19$). Points coloured by condition class. Dashed lines indicate linear trend.

The spatial distribution of the three dominant land cover categories was mapped in Figure 12, which shows forest cover, cropland proportion, and grassland proportion for each KHG. The three-panel view demonstrates the spatial complementarity between forest loss and agricultural gain: KHGs with low forest cover in the eastern lowlands correspond to those with high cropland proportions, while western and interior KHGs retain substantially more natural vegetation.

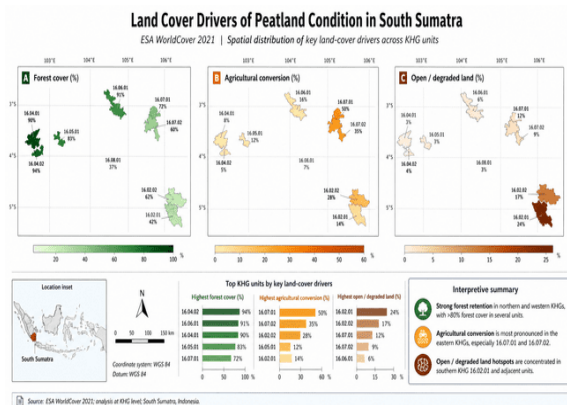


Figure 12. Spatial distribution of dominant land cover categories per KHG: forest and mangrove cover (left), cropland and plantation (centre), and grassland and open land (right). Labels show KHG code and percentage for each category.

Driver Decomposition and Limiting Factors

Decomposition of the weighted score contributions for the 2024 assessment was shown in Figure 13. Each horizontal bar represents a KHG, with segments coloured by indicator contribution (NDWI in blue, EVI in green, fire inverse in red, surface water in purple). The rightmost annotation for each KHG identifies its limiting factor — the indicator with the lowest normalized score. Surface water availability was the universal limiting factor across all twelve KHGs, indicating that, regardless of other conditions, low surface water extent consistently constrained composite scores. This finding was consistent with the widespread drainage of South Sumatran peatlands and supports the BRGM's emphasis on canal blocking and rewetting as the primary restoration intervention.

To visualise the multi-dimensional indicator profile of the most-contrasting KHGs, Figure 14 presents radar charts comparing the three healthiest and three most-degraded units. The Intact/Recovering units (green) show consistently high scores across NDWI, EVI, and fire dimensions, with surface water being the sole weak axis. The At Risk units (red) show a more collapsed profile, with depression across multiple indicators — particularly vegetation and fire — in addition to the universal water deficit. This multi-dimensional comparison reinforces the finding that while surface water was the universal constraint, the most degraded KHGs suffer from compounding pressures across multiple indicators simultaneously.

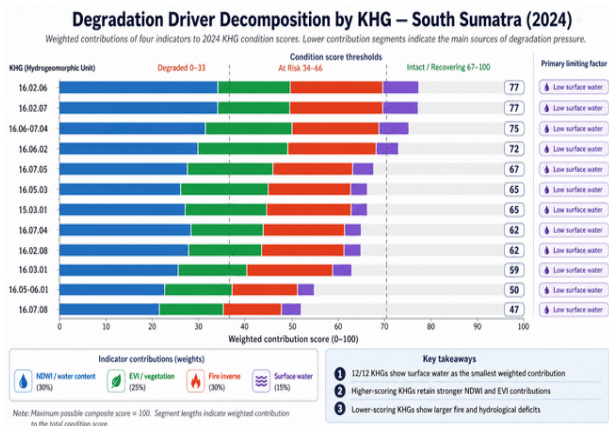


Figure 13. Degradation driver decomposition per KHG, 2024. Stacked bars show weighted contributions of each indicator: NDWI/water content (blue, 30%), EVI/vegetation (green, 25%), fire inverse (red, 30%), and surface water (purple, 15%). Right-side annotations identify the limiting factor for each unit.

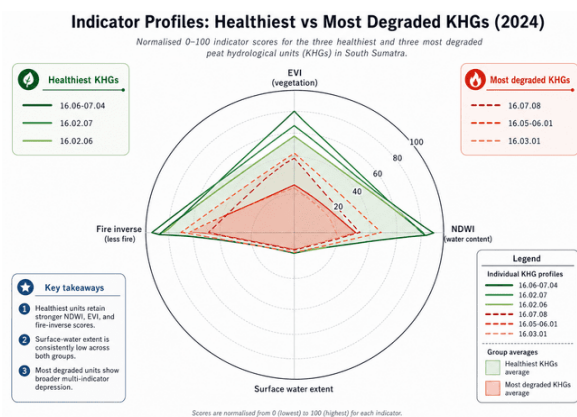


Figure 14. Radar chart comparing indicator profiles (normalized 0–100) for the three healthiest (green, solid) and three most-degraded (red, dashed) KHGs in 2024. Axes represent NDWI (water content), EVI (vegetation), fire inverse (fewer fires), and water extent. Intact units show consistently high scores except surface water; At Risk units show depression across multiple indicators.

Weight Sensitivity Analysis

The sensitivity of KHG classifications to alternative weighting scenarios was presented in Figure 15. We tested five weight combinations and showed the resulting scores for each KHG as grouped bars. Seven of twelve KHGs maintained the same condition classification regardless of the weight scenario applied, demonstrating that these units were robustly classified. Five KHGs changed classification under at least one scenario, predominantly shifting between At Risk and Intact/Recovering. KHG.16.07.08 was the only unit to fall into the Degraded category under any scenario (water-dominant weighting), confirming it as the most vulnerable unit in the study area. The maximum deviation from baseline scores across

any single KHG–scenario combination was 15.2 points, while the mean deviation was 6.8 points, indicating that the relative ranking and broad classification of units were robust even when weight assumptions were substantially altered.

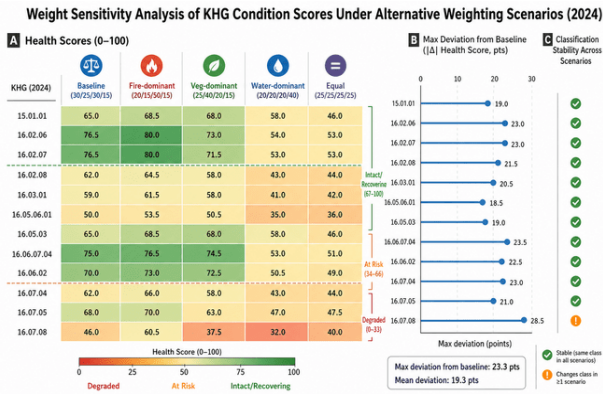


Figure 15. Weight sensitivity analysis showing health scores under five alternative weighting scenarios for each KHG in 2024. Scenarios: baseline (30/25/30/15), fire-dominant (20/15/50/15), vegetation-dominant (25/40/20/15), water-dominant (20/20/20/40), and equal weights (25/25/25/25). Dashed horizontal lines indicate classification thresholds.

The inter-relationships among indicators were further examined in Figure 16, which presents the

Pearson correlation matrix across all KHG–year observations. The strongest positive correlation was between NDWI and EVI ($r=0.62$), reflecting the expected coupling between peat moisture and vegetation vigour. Fire count showed a weak negative correlation with both NDWI and EVI, consistent with fire being an episodic disturbance rather than a continuous covariate. The composite health score showed the strongest correlation with fire inverse ($r=0.71$) and NDWI ($r=0.67$), confirming that the weight allocation appropriately reflects the empirical structure of the indicator relationships.

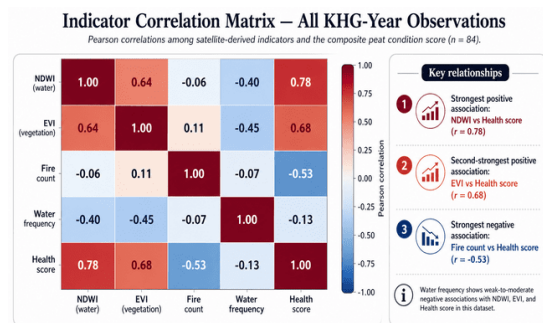


Figure 16. Pearson correlation matrix among the four satellite-derived indicators and composite health score across all KHG-year observations ($n = 84$). Color scale: blue (positive) to red (negative). Cell values indicate correlation coefficients.

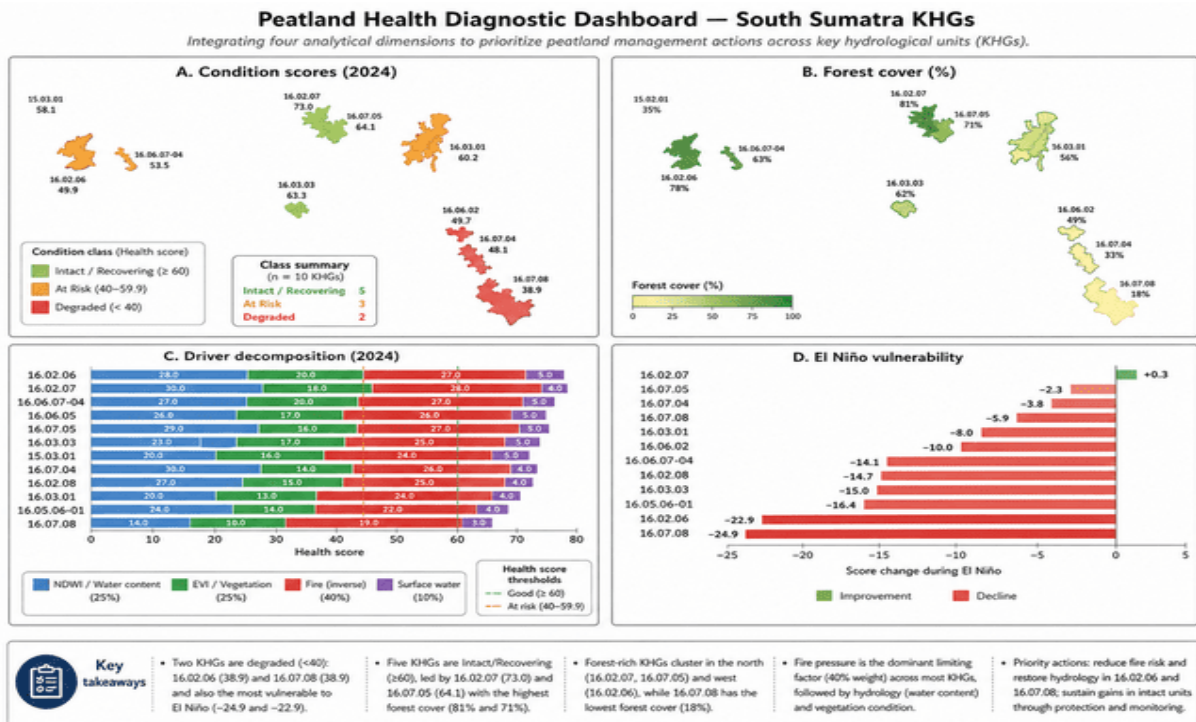


Figure 17. Diagnostic summary dashboard integrating four analytical dimensions: (A) spatial distribution of 2024 condition scores, (B) forest cover percentage per KHG, (C) weighted indicator contribution decomposition, and (D) El Niño vulnerability showing score drop during El Niño years. This combined view supports management prioritisation by identifying which KHGs were most degraded, why, and how climate-sensitive they are.

DISCUSSION

Framework Design and Positioning

The framework presented in this study should be interpreted as a KHG-scale screening and prioritisation tool rather than a field-grade diagnostic system. This distinction is important because the spatial resolution of the input datasets, including MODIS vegetation and moisture products, active fire detections, and surface-water context layers, cannot resolve fine-scale drainage canals, individual plantation blocks, small rewetting structures, or localised peat subsidence. Similar limitations have been recognised in remote-sensing-based wetland, peatland, and forest degradation monitoring, where satellite indicators are useful for detecting broad spatial patterns but still require field validation for site-level diagnosis (Mitchell et al., 2017; Lees et al., 2018; Dadap et al., 2019; Ghazaryan et al., 2024). Recent tropical peatland studies using optical and thermal remote sensing have also shown that satellite-derived moisture indicators can support water-table inference, but they remain proxy-based and need calibration against field measurements when used for hydrological diagnosis (Burdun et al., 2023; Koupaei-Abyazani et al., 2024).

Therefore, the main value of the framework is not to replace field surveys, but to identify which KHGs require closer investigation, restoration targeting, or seasonal fire-prevention planning. The 2024 results show that this screening function is meaningful. Seven of the twelve assessed KHGs were classified as At Risk, while five were classified as Intact/Recovering. No KHG fell into the Degraded class under the baseline weighting, but several At Risk units were clustered close to the lower-middle part of the scoring range. This suggests that the study area is not uniformly degraded, but neither is it uniformly secure. This pattern supports multi-indicator assessment because peatland condition is shaped by interacting hydrological, vegetation, fire, and land-cover processes rather than a single variable (Minasny et al., 2019; Cahyono et al., 2022; Omar et al., 2022).

Aligning the analytical unit with official KHG boundaries is also a deliberate, governance-oriented design choice. KHG-scale studies have

shown that peat hydrological units are relevant not only for ecological assessment, but also for ecosystem-service valuation, restoration planning, and institutional decision-making (Rossita et al., 2021; Cahyono et al., 2022). By producing condition scores directly at KHG scale, the framework translates satellite-derived information into a spatial unit that is more legible for peatland restoration planning, provincial environmental monitoring, and environmental baseline assessment.

Comparison with Existing Approaches

The composite scoring approach used in this study is conceptually related to GIS-based multi-criteria decision analysis, where heterogeneous environmental indicators are normalised, weighted, and integrated to support spatial prioritisation (Greco et al., 2019). It is also consistent with composite-indicator practice, where sensitivity analysis is needed to test whether rankings and classifications are robust to weighting assumptions (Greco et al., 2019). In the context of peatland restoration, Cahyono et al. (2022) combined hydrological, topographical, fire, vegetation, and remote-sensing variables to identify priority restoration areas for degraded tropical peatlands. Compared with that approach, the present framework is simpler and more operationally accessible because it relies on open satellite products, Google Earth Engine processing, and KHG-level aggregation rather than requiring more detailed hydrological or topographical input data. This makes the framework more suitable for rapid screening, although less precise than methods using field water-table measurements, peat depth, LiDAR, or high-resolution radar data (Minasny et al., 2019; Ghazaryan et al., 2024; Koupaei-Abyazani et al., 2024).

That trade-off is acceptable for provincial-scale screening because the framework uses freely available satellite data, cloud-based processing, and repeatable annual aggregation. Google Earth Engine has been widely used for large-scale geospatial analysis because it reduces the computational barrier for processing long satellite archives (Gorelick et al., 2017). However, the resulting classes should be interpreted as relative condition categories rather than absolute

ecological states. A KHG classified as Intact/Recovering may still contain localised degraded areas, while an At Risk KHG may contain pockets of recovering vegetation or successful rewetting. The framework's seven-year temporal depth is one of its main advantages because snapshot assessments cannot distinguish whether a KHG is chronically declining, recovering, or mainly sensitive to climate anomalies. This temporal framing is consistent with recent peatland studies showing that fire, land-cover change, moisture stress, and restoration response vary strongly across years and cannot be fully understood from a single-date assessment (Dadap et al., 2019; Vetruta & Cochrane, 2020; Irfan et al., 2024).

Implications for Peatland Management

Three management implications emerge from the results. First, the weak surface-water context signal and the importance of NDWI-based moisture variation reinforce the central role of hydrological restoration in tropical peatland management. Tropical peatland degradation is closely linked to drainage, water-table decline, oxidation, subsidence, carbon loss, and increased fire vulnerability (Dadap et al., 2019; Anshari et al., 2021; Dadap et al., 2021; Koupaie-Abyazani et al., 2024). In South Sumatra, Irfan et al. (2024) showed that hotspot occurrence is closely related to groundwater-level dynamics, supporting the use of hydrological indicators as an early-warning component for fire-prone peatlands. Rewetting through canal blocking and related hydrological restoration measures is therefore widely recognised as a key restoration strategy because raising water levels can reduce fire risk and create conditions for vegetation recovery (Yuwati et al., 2021; Lestari et al., 2024). In this study, the consistently weak surface-water context contribution should be interpreted as a screening-level hydrological signal rather than a direct water-table measurement, while annual moisture dynamics are better represented by the NDWI indicator.

Second, the divergent trajectory pattern indicates that restoration and degradation pressures are spatially uneven. The improvement of KHG.16.02.07 suggests that some units may be responding positively to restoration, land-

management change, or favourable hydrological conditions. However, the concurrent decline of other KHGs shows that recovery is not province-wide. This is consistent with broader evidence that Indonesian peatland condition is shaped by the combined effects of drainage, land-cover conversion, recurrent burning, and management history (Vetruta & Cochrane, 2020; Dadap et al., 2021; Omar et al., 2022). The negative association between cropland or plantation cover and condition score in this study should therefore be interpreted as an indicator of land-cover pressure rather than direct causal proof. This cautious interpretation is important because open vegetation, shrubland, and bare land may represent different ecological states, including active degradation, post-fire regrowth, temporary exposure, or early recovery (Vetruta & Cochrane, 2020; Cahyono et al., 2022).

Third, the El Niño analysis shows that some KHGs require climate-sensitive management even when their average condition appears acceptable. The average score dropped by 11.3 points during El Niño years, but responses varied strongly among units. KHG.16.06-07.04 dropped by 24.9 points during El Niño years despite retaining substantial forest cover, indicating that vegetation cover alone may not guarantee resilience under drought stress. This finding is consistent with studies showing that peat fire risk is strongly controlled by moisture deficit, groundwater decline, and climate anomalies rather than land cover alone (Dadap et al., 2019; Vetruta & Cochrane, 2020; Nurhayati et al., 2021; Irfan et al., 2024). Management should therefore prioritise not only KHGs with low current condition scores, but also KHGs with high climate sensitivity. These units may require pre-El Niño interventions such as canal inspection, water-retention checks, intensified fire patrols, and hotspot early warning.

The diagnostic dashboard in Figure 17 is therefore useful because it combines four decision-relevant dimensions: current condition, forest cover, limiting indicators, and El Niño vulnerability. This integrated view helps avoid overly simplistic prioritisation. For example, a KHG with low current score and high cropland cover may require land-use control and rewetting attention, whereas a forested but El Niño-sensitive KHG may require seasonal fire-prevention

measures. Similarly, a KHG showing improvement should not automatically be deprioritised because continued monitoring is needed to confirm whether the recovery trend is stable or temporary. This logic is consistent with composite-indicator and restoration-prioritisation approaches, where a management-relevant index should not only rank units but also explain why units differ and how intervention strategies may vary (Greco et al., 2019; Cahyono et al., 2022; Lestari et al., 2024). In this sense, the framework provides a practical bridge between satellite monitoring and adaptive peatland management.

Limitations

Several limitations should be acknowledged. First, the 12 KHGs assessed in this study represent a subset of the wider KHG system in South Sumatra, constrained by the available boundary dataset. A province-wide assessment would require complete and harmonised KHG boundaries. Second, the min–max normalisation means that the condition score is relative to the observed range rather than anchored to field-validated ecological thresholds. Third, the 500 m resolution of the NDWI input smooths over within-KHG heterogeneity, and small KHGs with few pixels may produce less reliable aggregate statistics. These constraints are common in regional remote-sensing assessments, where broad spatial coverage is obtained at the cost of fine-scale diagnostic precision (Mitchell et al., 2017; Lees et al., 2018; Minasny et al., 2019; Ghazaryan et al., 2024).

Fourth, the absence of ground-truth validation data means that condition classifications have not been verified against direct field observations. Future work should integrate water-table depth, peat subsidence, canal density, and higher-resolution optical or radar imagery to calibrate the remote-sensing indicators against measured peatland condition (Anshari et al., 2021; Dadap et al., 2021; Koupaei-Abyazani et al., 2024).

CONCLUSION

This study developed and applied an open-data, multi-indicator remote sensing framework for assessing peatland condition at the KHG scale in South Sumatra. Using NDWI, EVI, fire

frequency, and surface water extent from 2018 to 2024, the framework classified seven of twelve KHGs as At Risk and five as Intact/Recovering in 2024. The temporal analysis showed divergent trajectories, with six KHGs declining, five improving, and one remaining relatively stable, indicating that peatland condition varies substantially across hydrological units. Cropland conversion was the strongest land-cover predictor of lower health scores ($r=-0.52$), while surface water availability was the limiting factor across all KHGs, highlighting the importance of hydrological restoration. El Niño years reduced scores by an average of 11.3 points, confirming climate-sensitive vulnerability. Weight sensitivity analysis showed that seven of twelve classifications remained stable across alternative weighting scenarios. Overall, the framework provides a reproducible screening tool for KHG-scale restoration prioritisation, while future work should integrate field validation, peat subsidence data, and higher-resolution imagery.

ACKNOWLEDGEMENTS

The author acknowledges the open satellite data and geospatial services provided by NASA FIRMS, MODIS, JRC Global Surface Water, ESA WorldCover, Google Earth Engine, KLHK, BRGM, and the South Sumatra peatland data portal. The author also acknowledges AI-assisted tools for supporting code development, data processing, and manuscript preparation, while retaining full responsibility for the accuracy, integrity, and originality of the final manuscript.

REFERENCES

- Anshari, G. Z., Gusmayanti, E., & Novita, N. (2021). The use of subsidence to estimate carbon loss from deforested and drained tropical peatlands in Indonesia. *Forests*, 12 (6), 1–19. <https://doi.org/10.3390/f12060732>
- Burdun, I., Bechtold, M., Aurela, M., De Lannoy, G. J. M., Desai, A. R., Humphreys, E., Kareksela, S., Komisarenko, V., Liimatainen, M., Marttila, H., Minkinen, K., Nilsson, M. B., Ojanen, P., Salko, S.-S., Tuittila, E.-S., Uemaa, E., & Rautiainen, M. (2023). Hidden becomes clear: Optical remote sensing of vegetation reveals water table dynamics in northern peatlands. *Remote Sensing of Environment*, 296 (113736), 1–14. <https://doi.org/10.1016/j.rse.2023.113736>
- BRGM (Peatland and Mangrove Restoration Agency). (2021). *Strategic plan of the Peatland and Mangrove Restoration Agency 2021–2024*. Peatland and Mangrove Restoration Agency.

- Cahyono, B. K., Aditya, T., & Istarno. (2022). The determination of priority areas for the restoration of degraded tropical peatland using hydrological, topographical, and remote sensing approaches. *Land*, 11 (7), 1094, 1–30. <https://doi.org/10.3390/land11071094>
- Crippa, P., Castruccio, S., Archer-Nicholls, S., Lebron, G. B., Kuwata, M., Thota, A., Sumin, S., Butt, E., Wiedinmyer, C., & Spracklen, D. V. (2016). Population exposure to hazardous air quality due to the 2015 fires in Equatorial Asia. *Scientific Reports*, 6 (37074), 1–9. <https://doi.org/10.1038/srep37074>
- Dadap, N. C., Cobb, A. R., Hoyt, A. M., Harvey, C. F., & Konings, A. G. (2019). Satellite soil moisture observations predict burned area in Southeast Asian peatlands. *Environmental Research Letters*, 14 (9), 094014, 1–10. <https://doi.org/10.1088/1748-9326/ab3891>
- Dadap, N. C., Hoyt, A. M., Cobb, A. R., Oner, D., Kozinski, M., Fua, P. V., Rao, K., Harvey, C. F., & Konings, A. G. (2021). Drainage canals in Southeast Asian peatlands increase carbon emissions. *AGU Advances*, 2 (1), 1–14. <https://doi.org/10.1029/2020AV000321>
- Didan, K. (2021). *MOD13Q1 MODIS/Terra vegetation indices 16-day L3 global 250m SIN grid V061* [Data set]. NASA EOSDIS Land Processes DAAC. Vegetation Index and Phenology Lab. The University of Arizona. (pp. 1–29). <https://doi.org/10.5067/MODIS/MOD13Q1.061>
- Ghazaryan, G., Krupp, L., Seyfried, S., Landgraf, N., & Nendel, C. (2024). Enhancing peatland monitoring through multisource remote sensing: Optical and radar data applications. *International Journal of Remote Sensing*, 45 (18), 6372–6394. <https://doi.org/10.1080/01431161.2024.2387133>
- Giglio, L., Schroeder, W., & Justice, C. O. (2016). The Collection 6 MODIS active fire detection algorithm and fire products. *Remote Sensing of Environment*, 178, 31–41. <https://doi.org/10.1016/j.rse.2016.02.054>
- Gorelick, N., Hancher, M., Dixon, M., Ilyushchenko, S., Thau, D., & Moore, R. (2017). Google Earth Engine: Planetary-scale geospatial analysis for everyone. *Remote Sensing of Environment*, 202, 18–27. <https://doi.org/10.1016/j.rse.2017.06.031>
- Greco, S., Ishizaka, A., Tasiou, M., & Torrisi, G. (2019). On the methodological framework of composite indices: A review of the issues of weighting, aggregation, and robustness. *Social Indicators Research*, 141, 61–94. <https://doi.org/10.1007/s11205-017-1832-9>
- Irfan, M., Koriyanti, E., Saleh, K., Hadi, Safrina, S., Awaludin, Sulaiman, A., Akhsan, H., Suhadi, Suwignyo, R. A., Choi, E., & Iskandar, I. (2024). Dynamics of peatland fires in South Sumatra in 2019: Role of groundwater levels, *Land*, 13 (3), 1–15. <https://doi.org/10.3390/land13030373>
- Koupaei-Abyazani, N., Burdun, I., Desai, A. R., Hergoualc'h, K., Hirano, T., Melling, L., Swails, E., Tang, A. C. I., & Wong, G. X. (2024). Tropical peatland water table estimations from space. *Journal of Geophysical Research: Biogeosciences*, 129 (6), 1–22. <https://doi.org/10.1029/2024JG008116>
- KLHK (Ministry of Environment and Forestry of the Republic of Indonesia). (2017). *Decree of the Minister of Environment and Forestry of the Republic of Indonesia No. SK.129/MENLHK/SETJEN/PKL.0/2/2017 concerning the establishment of the national peat hydrological unit map* Ministry of Environment and Forestry of the Republic of Indonesia.
- Lees, K. J., Quaife, T., Artz, R. R. E., Khomik, M., & Clark, J. M. (2018). Potential for using remote sensing to estimate carbon fluxes across northern peatlands: A review. *Science of the Total Environment*, 615, 857–874. <https://doi.org/10.1016/j.scitotenv.2017.09.103>
- Lestari, N. S., Rochmayanto, Y., Salminah, M., Novita, N., Asyhari, A., Gangga, A., Ritonga, R., Yeo, S., & Albar, I. (2024). Opportunities and risk management of peat restoration in Indonesia: Lessons learned from peat restoration actors. *Restoration Ecology*, 32 (1), e14054, 1–14. <https://doi.org/10.1111/rec.14054>
- Miettinen, J., Shi, C., & Liew, S. C. (2016). Land cover distribution in the peatlands of Peninsular Malaysia, Sumatra and Borneo in 2015 with changes since 1990. *Global Ecology and Conservation*, 6, 67–78. <https://doi.org/10.1016/j.gecco.2016.02.004>
- Minasny, B., Berglund, Ö., Connolly, J., Hedley, C., de Vries, F., Gimona, A., Kempen, B., Kidd, D., Lilja, H., Malone, B., McBratney, A., Roudier, P., Rudiyanto, Padarian, J., Poggio, L., ten Caten, A., Thompson, D., Tuve, C., & Widyatmanti, W. (2019). Digital mapping of peatlands: A critical review. *Earth-Science Reviews*, 196(102870), 1–38. <https://doi.org/10.1016/j.earscirev.2019.05.014>
- Mitchell, A. L., Rosenqvist, A., & Mora, B. (2017). Current remote sensing approaches to monitoring forest degradation in support of countries measurement, reporting and verification systems for REDD+. *Carbon Balance and Management*, 12 (9), 1–22. <https://doi.org/10.1186/s13021-017-0078-9>
- Nurhayati, A. D., Saharjo, B. H., Sundawati, L., Syartinilia, & Cochrane, M. A. (2021). Forest and peatland fire dynamics in South Sumatra Province. *Forest and Society*, 5(2), 591–603. <https://doi.org/10.24259/fs.v5i2.14435>
- Omar, M. S., Ifandi, E., Sukri, R. S., Kalaitzidis, S., Christanis, K., Lai, D. T. C., & Tsikouras, B. (2022). Peatlands in Southeast Asia: A comprehensive geological review. *Earth-Science Reviews*, 232, 104–149. <https://doi.org/10.1016/j.earscirev.2022.104149>
- Pekel, J.-F., Cottam, A., Gorelick, N., & Belward, A. S. (2016). High-resolution mapping of global surface water and its long-term changes. *Nature*, 540, 418–422. <https://doi.org/10.1038/nature20584>
- Putra, R., Lestari, D. O., Sutriyono, E., Sabaruddin, & Iskandar, I. (2019). Dynamical link of peat fires in South Sumatra and the climate modes in the Indo-Pacific region. *Indonesian Journal of Geography*, 51 (1), 18–22. <https://doi.org/10.22146/ijg.35667>
- Rossita, A., Nurrochmat, D. R., Boer, R., Hein, L., & Riqqi, A. (2021). Assessing the monetary value of ecosystem services provided by Gaung-Batang Tuaka Peat Hydrological Unit (KHG), Riau Province. *Heliyon*, 7 (10), 1–11. <https://doi.org/10.1016/j.heliyon.2021.e08208>
- Tacconi, L. (2016). Preventing fires and haze in Southeast Asia. *Nature Climate Change*, 6, 640–643. <https://doi.org/10.1038/nclimate3008>
- United Nations Environment Programme. (2022). *Global peatlands assessment: The state of the world's peatlands: Evidence for action toward the conservation, restoration, and sustainable management of peatlands*. United Nations Environment Programme. <https://doi.org/10.59117/20.500.11822/41222>
- United Nations Office for Disaster Risk Reduction. (2024). *Indonesia wildfires, 2023: Forensic analysis*. United Nations Office for Disaster Risk Reduction.
- Vermote, E. (2021). *MOD09A1 MODIS/Terra surface reflectance 8-day L3 global 500m SIN grid V061* [Data set]. NASA EOSDIS Land Processes DAAC. <https://doi.org/10.5067/MODIS/MOD09A1.061>
- Vettrita, Y., & Cochrane, M. A. (2020). Fire frequency and related land-use and land-cover changes in Indonesia's peatlands. *Remote Sensing*, 12 (1), 1–23. <https://doi.org/10.3390/rs12010005>

- Yuwati, T. W., Rachmanadi, D., Pratiwi, Turjaman, M., Indrajaya, Y., Nugroho, H. Y. S. H., Qirom, M. A., Narendra, B. H., Winarno, B., Lestari, S., Santosa, P. B., Adi, R. N., Savitri, E., Putra, P. B., Saputra, D. D., Wahyuningtyas, R. S., Prayudyaningsih, R., Halwany, W., & Murniati. (2021). Restoration of degraded tropical peatland in Indonesia: A review. *Land*, 10 (1170), 1–31. <https://doi.org/10.3390/land10111170>
- Zanaga, D., Van De Kerchove, R., Daems, D., De Keersmaecker, W., Brockmann, C., Kirches, G., Wevers, J., Cartus, O., Santoro, M., Fritz, S., Lesiv, M., Herold, M., Tsendbazar, N. E., Xu, P., Ramoino, F., & Arino, O. (2022). *ESA WorldCover 10 m 2021 v200* [Data set]. Zenodo. <https://doi.org/10.5281/zenodo.7254221>