

Peat Burning Scales Super-linearly with Fire-Season Magnitude in the West Kalimantan–Sarawak Border Region, 2012–2025

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Abstract

Transboundary haze from Kalimantan, Indonesia, is a recurring air-quality hazard for Sarawak, Malaysia, and is disproportionately attributed to smouldering combustion of degraded tropical peatland. Using fourteen fire seasons (2012–2025) of VIIRS active-fire detections classified against a peatland extent map, I show that peat burning scales super-linearly with fire-season magnitude: annual peat-fire detections rise with total detections as a power law of exponent 1.96 (95% CI 1.57–2.36; $R^2 = 0.89$), so a doubling of fire activity accompanies an approximately four-fold rise in peat burning. The power law outperforms proportional, exponential and log-quadratic alternatives, holds when the disjoint non-peat count is substituted as predictor (exponent 2.36), and is reproduced on a sensor-homogeneous Suomi-NPP subset (1.98). The peat-fire share consequently climbs from under 4% in strong La Niña years to 30–51% in El Niño years and correlates with the Oceanic Niño Index ($r = 0.78$, $p = 0.0010$); because ONI and fire-season magnitude are strongly collinear ($r = 0.79$), however, these data cannot isolate a compositional effect of ENSO (partial $r = 0.29$, $p = 0.31$). Recurrently burning locations dominate cumulative emissions: 24.3% of affected 0.05° cells burned in seven or more years yet contributed 57.7% of cumulative fire radiative power. Back-trajectory analysis shows the scaling survives transport to twelve Sarawak receptors (exponent 1.59) while the ENSO signal attenuates. Because peat emits more particulate matter per unit fuel, haze burden grows considerably faster than fire count.

Introduction

Seasonal transboundary haze from vegetation and peatland fires in Sumatra and Kalimantan is one of the most persistent environmental and public-health problems in maritime Southeast Asia, affecting Indonesia, Malaysia, Singapore, and Brunei almost every dry season (Field et al., 2016; Huijnen et al., 2016). Tropical peatlands, although covering a minority of the burned landscape in Sumatra and Kalimantan, contribute disproportionately to emissions: their smouldering, low-temperature combustion is far less complete than the flaming combustion of above-ground vegetation and releases substantially more particulate matter per unit of fuel consumed, as field measurements of peat-fire emission factors in Central Kalimantan during the 2015 El Niño confirm (Stockwell et al., 2016). Carbon emissions from that 2015 season were the largest recorded in the region since 1997 (Huijnen et al., 2016). The problem is not receding. As this manuscript was being prepared, the 2026 fire season developed into a severe transboundary haze episode, and on 5 September the Malaysian government declared a state of emergency in Serian Division, Sarawak, on air-quality grounds (Al Jazeera, 2026). In my own processing of the near-real-time satellite record, 2026 had by 7 September already surpassed every season in the fourteen-year VIIRS archive for the equivalent calendar window, with more than seven weeks of the season still to run (see “The ongoing 2026 season”).

The El Niño–Southern Oscillation (ENSO) is the dominant driver of interannual variability in fire activity across Borneo: El Niño years suppress the rainfall that normally keeps the peat water table high (Wooster et al., 2012), and the resulting drawdown makes peat soils flammable at depth: monitoring at six restoration-agency stations in South Sumatran peatland found hotspot numbers rising as

groundwater levels fell, and recommended holding the water table within roughly half a metre of the surface to suppress ignition (Irfan et al., 2024). This mechanism is well described qualitatively, and the two most severe fire and haze crises on record, 1997 and 2015, both coincided with strong El Niño conditions (Field et al., 2016). A third major regional haze crisis, in 2019, occurred despite only weakly positive ENSO conditions that year (see “Interannual variability in fire activity and its relationship with ENSO”), and severe Bornean fires have more generally been documented under weak or even negative ENSO conditions, indicating that ENSO strength alone does not linearly predict total burned area or total emissions (Lam et al., 2026).

Two more specific questions remain comparatively under-quantified in the published literature. First, does ENSO intensity shift not only the total amount of fire activity but also its composition — that is, the share of fires occurring specifically on peat versus mineral soil — in a way that can be expressed as a continuous, testable statistical relationship rather than a qualitative association or a single-event case study? Second, given that peatland fire monitoring reports increasingly describe a shift from episodic mega-fires toward recurrent annual burning at particular locations, how concentrated is cumulative fire radiative power (FRP, a proxy for emitted energy and, by extension, smoke) among the subset of locations that burn repeatedly, as opposed to locations that burn only once in a multi-year record?

A further consideration is that Indonesia's fire and peatland governance landscape changed substantially over the study period. Following the record-breaking 2015 fire season, the Government of Indonesia established the Peatland Restoration Agency (Badan Restorasi Gambut, BRG) in January 2016, with a mandate to rewet, revegetate, and revitalize 2 million hectares of degraded peatland by 2020 through large-scale canal-blocking infrastructure; a successor agency (BRGM) extended this mandate from 2021 (Castro et al., 2026). Whether this policy shift is detectable as a change in the strength of the ENSO–fire relationship at the landscape scale — as opposed to at the level of individual, well-documented restoration sites — has not, to my knowledge, previously been tested. Malaysia's own peatland fire management operates largely independently of these Indonesian source-side drivers: a recent survey-based assessment of peatland fire management in Malaysia identified persistent gaps in prevention and suppression policy and practice on the receiving side of the transboundary haze system, underscoring that quantifying the upstream ENSO–peat-fire relationship in Kalimantan remains central to anticipating haze reaching Sarawak (Musa et al., 2026).

This study addresses these questions using a purpose-built, harmonised dataset of satellite fire detections, a peatland extent map, and the Oceanic Niño Index (ONI) for the 2012–2025 Southeast Asian fire season (July–October) in the West/Central Kalimantan – Sarawak border region. My objectives are: (i) to quantify the relationship between ENSO intensity and the peat-fire share of total fire detections across fourteen fire seasons; (ii) to quantify the spatial concentration of cumulative FRP among recurrently burning peatland locations, situating this second result explicitly against the closest prior work, Vetrina and Cochrane's (2020) two-decade, MODIS-based analysis of recurrent peatland burning in Sumatra and Kalimantan; (iii) to explore, descriptively, whether the ENSO–composition relationship has changed since the onset of national peatland restoration policy in 2016, and whether it varies with

distance from the Sarawak border; and (iv) to assess, using an independent, non-VIIRS sensor, whether the ENSO–composition relationship is also detectable in the eleven fire seasons preceding the VIIRS record.

Materials and methods

Study area and data sources

The study domain spans 107.0–116.5°E and – 4.0–6.0°N, covering West, Central, and parts of South and North Kalimantan (Indonesia) and the whole of Sarawak (Malaysia). Active-fire detections were obtained from the NASA Fire Information for Resource Management System (FIRMS) Area API, using the VIIRS 375 m Standard Product (Collection 2), for 1 July–31 October of each year from 2012 to 2025 (NASA FIRMS, 2026a). The number of VIIRS-carrying platforms in orbit grew over the study period: Suomi-NPP (SNPP) alone for 2012–2017, joined by NOAA-20 from 2018 and by NOAA-21 from 2024. The pooled record therefore rests on one, two and three near-identical sensors in successive sub-periods, which inflates absolute detection counts independently of any change in fire activity. Rather than attempt a cross-sensor correction, I address this in two ways: the principal analysis uses a ratio metric, which is far less sensitive to the number of platforms than the absolute counts shown in Table 1; and every principal analysis is repeated on the SNPP-only subset, which is sensor-homogeneous across all fourteen years (see “Sensor-homogeneous replication”). Each detection record includes latitude, longitude, fire radiative power (FRP, MW), acquisition date/time (UTC), and a per-pixel confidence flag. Peatland extent was obtained from PEATMAP, a global compilation of the highest-resolution available regional and national peatland maps (Xu et al., 2018).

Table 1
Annual fire activity, peat-fire share, and haze-season ONI, 2012–2025.

Year	ONI (JAS–SON mean, °C)	Total fire detections	Peat-fire detections	Peat-fire share	Total FRP (MW)
2012*	0.35	95,537	34,207	35.8%	1,066,825
2013*	–0.27	57,123	12,797	22.4%	745,120
2014*	0.27	158,944	56,801	35.7%	1,588,705
2015*	2.01	325,827	148,392	45.5%	2,593,902
2016*	–0.42	25,917	2,845	11.0%	334,245
2017*	–0.25	17,607	1,272	7.2%	173,993
2018	0.55	120,865	41,147	34.0%	1,263,361
2019	0.34	305,499	154,907	50.7%	2,636,325
2020	–0.73	33,846	594	1.8%	361,061
2021	–0.62	28,856	1,057	3.7%	268,575
2022	–0.85	22,614	573	2.5%	221,841
2023	1.50	152,836	46,217	30.2%	1,418,389
2024	–0.12	80,289	5,512	6.9%	927,805
2025	–0.42	86,443	7,239	8.4%	1,013,474
* Number of VIIRS platforms contributing detections: Suomi-NPP alone for 2012–2017, joined by NOAA-20 from 2018 and by NOAA-21 from 2024 (see “Study area and data sources”). Absolute counts are therefore not comparable across these sub-periods; the sensor-homogeneous replication is reported in the “The interannual results are unchanged under a sensor-homogeneous replication” section.					

Fire–peatland classification

Each fire detection was spatially joined to the PEATMAP polygon layer (point-in-polygon test) and flagged as a peat fire if it fell within a mapped peatland boundary, and as a non-peat fire otherwise. A total of 1,512,203 fire detections were classified across the fourteen fire seasons, of which 513,560 (34.0%) were located on mapped peatland.

ENSO index and haze-season definition

Interannual ENSO state was represented by the Oceanic Niño Index (ONI), the running 3-month mean sea-surface-temperature anomaly in the Niño 3.4 region, obtained from the NOAA Climate Prediction Center (NOAA Climate Prediction Center, 2026). Because the study period spans the months of July

through October, each year was assigned a single haze-season ONI value equal to the mean of the three overlapping seasonal values that cover this window (JAS, ASO, and SON).

Statistical analysis of the ENSO–peat-fire-share relationship

For each year, the peat-fire share was computed as the number of peat-classified detections divided by the total number of detections. The relationship between the haze-season ONI and the peat-fire share was assessed using Pearson product-moment correlation and, as a robustness check against the influence of any single extreme year, Spearman rank correlation. Because the sample size at the annual level is nonetheless modest ($n = 14$), a leave-one-year-out sensitivity analysis was additionally performed, recomputing the Pearson correlation fourteen times, each time excluding one year, to verify that the relationship was not driven by a single influential observation.

Because ENSO also drives the total volume of fire activity, a correlation between ONI and the peat-fire share cannot by itself establish that ENSO acts on fire composition independently of fire-season magnitude. Two further analyses were therefore performed. First, the partial correlation between ONI and the peat-fire share was computed controlling for the log of total annual fire detections, together with the corresponding multiple regression, to test whether ONI retains explanatory power once fire-season magnitude is accounted for. Second, the scaling of peat burning with fire-season magnitude was estimated directly by regressing the log of annual peat-fire detections on the log of annual total detections; the fitted slope is the power-law exponent b in $(\text{peat detections}) \propto (\text{total detections})^b$, and a one-sided t -test of $b > 1$ was used to test whether peat burning grows disproportionately faster than fire activity as a whole. The same exponent was estimated from fire radiative power in place of detection counts, and its stability assessed by leave-one-year-out. Three further checks were applied to this scaling model. First, the power law was compared against three alternative functional forms for the same response — proportional scaling with the exponent fixed at unity, an exponential form, and a log-quadratic form allowing the log–log relationship to curve — using the Akaike information criterion with small-sample correction (AICc). Second, because total detections contain peat detections by construction, the regression was repeated with the disjoint non-peat detection count as the predictor, so that any super-linearity cannot arise from the shared variable alone. Third, residuals were examined for normality (Shapiro–Wilk), homoscedasticity (Breusch–Pagan), serial correlation (Durbin–Watson) and influential years (Cook’s distance), and the exponent was re-tested using heteroscedasticity- and autocorrelation-consistent (Newey–West HAC) standard errors.

Spatial recurrence analysis

Peat-classified fire detections were aggregated onto a regular $0.05^\circ \times 0.05^\circ$ grid (approximately 5.5 km $\times$ 5.5 km at the equator). For every grid cell that contained at least one peat-fire detection at any point in the fourteen-year record, I computed (a) the number of distinct calendar years in which the cell recorded at least one detection (1–14), and (b) the cumulative FRP summed across all peat-fire detections within that cell over the full record. Cells were then grouped into four recurrence categories (1 year; 2–4 years;

5–6 years; 7–14 years) and the share of total cells and the share of cumulative FRP were computed for each category.

Restoration-era comparison

To test whether the ENSO–peat-fire-share relationship changed after the January 2016 establishment of BRG, the fourteen-year record was split into a pre-restoration period (2012–2015, $n = 4$) and a post-restoration period (2016–2025, $n = 10$), and the ordinary least-squares slope of peat-fire share on haze-season ONI was compared between the two periods. A pooled regression with an $\text{ONI} \times \text{period}$ interaction term was additionally fitted to formally test whether the two slopes differed.

Distance-to-border sensitivity

Because the perpendicular distance from each fire detection to the Sarawak state boundary (`dist_to_sarawak_km`) was already computed during fire-level dataset construction, using the GADM Level-1 administrative boundary for Sarawak, the year-level ENSO–peat-fire-share analysis (see “Statistical analysis of the ENSO–peat-fire-share relationship”) was repeated after restricting the fire-detection pool to progressively narrower distance bands (≤ 200 km, ≤ 100 km, and ≤ 50 km from the border), to test whether the relationship strengthens or weakens closer to the transboundary corridor most directly relevant to haze reaching Sarawak.

MODIS-era robustness check (2001–2011)

To assess whether the ENSO–peat-fire-share relationship extends beyond the fourteen-year VIIRS record and to provide a check that does not depend on VIIRS instrument characteristics, active-fire detections for the same domain and July–October window were additionally obtained from the FIRMS Area API using the MODIS Standard Product (Terra and Aqua combined) for 2001–2011, the eleven fire seasons immediately preceding the start of Suomi-NPP VIIRS operations (NASA FIRMS, 2026b). Coverage was confirmed to begin reliably in November 2000, so full haze-season data were only available from 2001 onward. These MODIS detections were classified against PEATMAP and correlated with haze-season ONI using the same procedure as the “Statistical analysis of the ENSO–peat-fire-share relationship” section, but were deliberately not pooled with the VIIRS-based 2012–2025 series in any single regression, because MODIS's 1 km nominal fire-pixel resolution and known lower sensitivity to small, low-temperature smouldering fires — directly demonstrated by comparison against a higher-sensitivity experimental sensor during the 2015 Central Kalimantan fire season (Atwood et al., 2016) — make its detection counts not directly comparable in magnitude to VIIRS 375 m detections; the MODIS-era result is therefore reported and interpreted strictly as an independent, sensor-separate check on the direction of the relationship rather than as an extension of the fourteen-year time series.

Sensor-homogeneous replication

To establish that none of the interannual results depends on the growth in the number of VIIRS platforms described in the “Study area and data sources” section, the peat-fire-share correlation, the leave-one-

year-out sensitivity analysis, the partial correlation and the scaling exponent were all recomputed on detections from Suomi-NPP alone. SNPP operated continuously throughout 2012–2025, so this subset (1,068,773 detections) is homogeneous with respect to platform count across the entire record, at the cost of discarding roughly 29% of the pooled detections.

Transport-weighted fire exposure at Sarawak receptors

The analyses above characterise fire composition at the source. To connect them to smoke actually arriving in Sarawak, 72-hour backward trajectories were computed with the HYSPLIT model (Stein et al., 2015) from twelve Sarawak receptor sites (Bintulu, Kapit, Kuching, Limbang, Miri, ILP Miri, Mukah, Samalaju, Samarahan, Sarikei, Sibu and Sri Aman), released at 10 m above ground level four times daily (00, 06, 12 and 18 UTC) for 1 July–31 October of each year from 2018 to 2025, driven by GDAS meteorology – 47,040 trajectories in total. Trajectories were computed only from 2018 onward because the archived meteorological fields required for the earlier seasons were not retained. Each fire detection lying within 100 km of a trajectory point, and within ± 1 hour of the time at which the air parcel occupied that point, was attributed to that trajectory; fire radiative power was then accumulated separately over peat and non-peat detections to give a transport-weighted fire exposure for each receptor and release time. Summing across all twelve receptors gives, for each year, the peat share of transport-weighted exposure – the fraction of the fire signal reaching Sarawak that originates on peatland. This quantity is a transport-weighted proxy rather than a measured particulate concentration: it does not represent plume dispersion, deposition, chemical ageing or injection height, and it should be read as an index of upwind fire influence rather than of air quality as experienced at the ground. Because the 100 km search radius and 72-hour trajectory length are analyst choices, the attribution was repeated across twelve configurations – four radii (50, 100, 150 and 200 km) crossed with three trajectory lengths (24, 48 and 72 h, obtained by truncating the computed trajectories at the corresponding transit age) – and every receptor-side result recomputed for each (Table 3). The release height (10 m above ground level) and the driving meteorology could not be varied, since altering them requires re-running HYSPLIT and the archived meteorological fields have not been retained; the ± 1 hour matching window was held fixed.

Table 3

Sensitivity of the receptor-side results (see “The scaling relationship survives transport to Sarawak”) to the search radius and trajectory length. Correlations are Pearson coefficients over the eight fire seasons 2018–2025; the exponent is that of transport-weighted peat exposure against total exposure, with the one-sided p-value for $b > 1$.

Radius (km)	Trajectory (h)	Mean peat share	r vs ONI	r vs source share	Exponent b (vs 1)
50	24	8.5%	0.40 (p = 0.32)	0.83	1.53 (p = 0.025)
50	48	8.3%	0.44 (p = 0.28)	0.89	1.41 (p = 0.067)
50	72	9.5%	0.44 (p = 0.27)	0.90	1.47 (p = 0.060)
100	24	7.5%	0.39 (p = 0.34)	0.72	1.68 (p = 0.026)
100	48	8.6%	0.41 (p = 0.32)	0.82	1.55 (p = 0.046)
100	72	10.0%	0.44 (p = 0.27)	0.88	1.59 (p = 0.042)
150	24	7.5%	0.42 (p = 0.30)	0.69	1.89 (p = 0.017)
150	48	8.4%	0.44 (p = 0.28)	0.83	1.67 (p = 0.035)
150	72	9.8%	0.45 (p = 0.26)	0.89	1.65 (p = 0.039)
200	24	7.6%	0.51 (p = 0.20)	0.77	1.96 (p = 0.014)
200	48	8.4%	0.51 (p = 0.19)	0.87	1.78 (p = 0.021)
200	72	9.5%	0.51 (p = 0.19)	0.93	1.75 (p = 0.026)

Software, statistical conventions and use of AI tools

All data processing and statistical analysis were carried out in Python. Tabular processing and statistics used pandas 2.3.3, NumPy 2.4.2, SciPy 1.17.0 and statsmodels 0.14.6 under Python 3.14.3; spatial operations — point-in-polygon peat classification, grid aggregation and boundary geometry — and all figure generation used GeoPandas 1.1.4, Shapely 2.1.2 and Matplotlib 3.11.1 under Python 3.13.7. Backward trajectories were computed with the HYSPLIT model (desktop version, March 2025 release) (Stein et al., 2015). Correlations are Pearson product-moment and Spearman rank coefficients as stated in each case; regressions are ordinary least squares. All reported p-values are two-sided, with the single

exception of the tests of the scaling exponent against unity (Sections 3.2, 3.3 and 3.8), which are one-sided as indicated.

An AI assistant (Anthropic Claude) was used to draft and revise the analysis scripts implementing the procedures described in this section, and to draft and revise the text of this manuscript. The author reviewed and verified all analyses, results and text, and takes full responsibility for the content of this manuscript.

The ongoing 2026 fire season

While this manuscript was being prepared, the 2026 fire season developed into a severe transboundary haze episode. To place it in the context of the fourteen-year record, VIIRS detections for the same domain were obtained for 1 July onward using the near-real-time (NRT) product, which is available at shorter latency than the Standard Product used for 2012–2025 (NASA FIRMS, 2026a) but is subject to less complete quality control. Because the 2026 season was incomplete at the time of analysis and rests on a different product, it is not pooled with the principal series. To bring the comparison as close as the data allow, all years are restricted to the same calendar window (1 July to 7 September, the last date available for 2026) and to Suomi-NPP alone, which controls for season length and for platform count. The difference in product cannot be controlled in the same way, and it is not neutral with respect to the comparison: NRT screening is less complete than that of the reprocessed Standard Product and would, if anything, be expected to yield somewhat more detections for equivalent fire activity. Any excess of 2026 over earlier seasons should therefore be read as an upper bound rather than as a measured difference. The magnitude of this bias could not be quantified directly: the Standard Product had not been released for any part of 2026 at the time of analysis, and the NRT archive does not reach back far enough to overlap the Standard Product record. Peat classification follows the “Fire–peatland classification” section unchanged.

Results

Interannual variability in fire activity and its relationship with ENSO

Total fire detections varied more than eighteen-fold across the fourteen fire seasons, from 17,607 in 2017 (a weak La Niña year, ONI = −0.25) to 325,827 in 2015 (a very strong El Niño year, ONI = 2.01) (Table 1, Fig. 1a), and total detection counts were themselves strongly and significantly correlated with the haze-season ONI (Pearson $r = 0.79$, $p = 0.0008$; Spearman $\rho = 0.81$, $p = 0.0005$). This aggregate relationship was nonetheless imperfectly monotonic at the level of individual years: 2019 (ONI = 0.34, a comparatively weak positive anomaly) recorded more fire detections than 2023, the second-strongest El Niño year in the record (ONI = 1.50), consistent with prior reports that fire activity in Kalimantan can be substantial even outside the strongest El Niño years. Absolute detection counts are not comparable on a like-for-like basis across the record, because the number of VIIRS platforms in orbit rose from one to two in 2018 and to three in 2024 (see “Study area and data sources”); a sensor-homogeneous replication of

all interannual results is reported in the “The interannual results are unchanged under a sensor-homogeneous replication” section.

A related, and less sensor-dependent, pattern emerged in fire composition. The peat-fire share of all detections ranged from 1.8% (2020, ONI = - 0.73) to 50.7% (2019) (Table 1, Fig. 1b). Every year with a positive haze-season ONI (2012, 2014, 2015, 2018, 2019, 2023) showed a peat-fire share above 30%, while all eight years with negative ONI showed shares below 23%, and six of those eight showed shares below 9%. The relationship between the haze-season ONI and the peat-fire share was strong and highly statistically significant across the full fourteen-year record (Pearson $r = 0.78$, $p = 0.0010$, $n = 14$; Fig. 2). A Spearman rank correlation, less sensitive to the magnitude of any single point, was similarly strong ($\rho = 0.83$, $p = 0.0003$). Decomposing the share into its two components shows that peat-fire and non-peat-fire counts individually also correlate strongly with ONI (peat: $r = 0.73$, $p = 0.0031$, $\rho = 0.87$; non-peat: $r = 0.82$, $p = 0.0003$, $\rho = 0.78$); ENSO intensity is therefore associated with a broad increase in fire activity across land-cover types, not a peat-specific volumetric signal in isolation. In a leave-one-year-out sensitivity analysis, the Pearson correlation between ONI and peat-fire share remained positive, strong, and significant ($p \leq 0.004$ in every case) after excluding any single year (range: $r = 0.745$ – 0.852 across the fourteen exclusions), indicating that the relationship is not an artefact of any one extreme year.

Peat burning scales super-linearly with fire-season magnitude

Because ENSO drives fire-season magnitude as well as composition — haze-season ONI and the log of total annual detections are themselves strongly correlated ($r = 0.79$, $p = 0.0008$) — the two effects cannot be assumed to be independent. Testing this directly, the partial correlation between ONI and the peat-fire share, controlling for the log of total annual detections, was weak and far from significant (partial $r = 0.29$, $p = 0.31$), and in the corresponding multiple regression the ONI term carried no detectable independent signal while fire-season magnitude did (ONI: coefficient 4.7 percentage points per unit ONI, $p = 0.334$; log total detections: 12.6 percentage points per e-fold, $p = 0.010$; adjusted $R^2 = 0.752$). With $n = 14$ and the two predictors this strongly collinear, these data cannot separate a compositional effect of ENSO from its volumetric effect; I therefore do not claim one.

What the record does resolve sharply is how peat burning scales with fire-season magnitude. Regressing the log of annual peat-fire detections on the log of annual total detections yields a power-law exponent of 1.96 (95% CI 1.57–2.36; $R^2 = 0.889$; Fig. 3), significantly steeper than the proportional expectation of unity (one-sided t-test, $p = 0.0002$): when total fire activity doubles, peat-fire detections rise roughly four-fold. The exponent estimated from fire radiative power rather than detection counts is effectively identical (2.01, $p = 0.0003$ against unity), and leave-one-year-out re-estimation leaves it within 1.87–2.09. The peat-fire share is consequently predicted more tightly by fire-season magnitude ($r = 0.88$ against log total detections, $p = 0.00004$) than by ONI itself ($r = 0.78$). This scaling relationship, rather than any separable compositional sensitivity to ENSO, is the mechanism by which El Niño years become disproportionately peat-dominated.

Three checks support the power law as the appropriate description of this relationship. Against alternative functional forms for the same response, it was the best-supported model by AICc, with proportional scaling (exponent fixed at unity) and an exponential form both decisively worse ($\Delta\text{AICc} = 11.7$ and 11.5 respectively) and a log-quadratic form penalised for its extra parameter without improving fit ($\Delta\text{AICc} = 4.0$; quadratic coefficient $p = 0.85$, so the log–log relationship shows no detectable curvature). Because total detections contain peat detections by construction, the regression was repeated using the disjoint non-peat count as the predictor: the exponent was, if anything, steeper (2.36 , 95% CI $1.70\text{--}3.01$; $R^2 = 0.806$; one-sided $p = 0.0008$ against unity), so the super-linearity is not an artefact of the shared variable. Residual diagnostics indicated normal residuals (Shapiro–Wilk $p = 0.36$) and no unduly influential year (all Cook’s distances below $4/n$), but did flag mild heteroscedasticity (Breusch–Pagan $p = 0.045$) and positive serial correlation (Durbin–Watson $= 0.94$), as might be expected from multi-year persistence in drought and land-use conditions. Re-estimating with Newey–West standard errors robust to both left the inference essentially unchanged ($b = 1.96$, HAC standard error $0.19\text{--}0.21$ depending on lag, one-sided $p = 0.0001\text{--}0.0003$ against unity).

The interannual results are unchanged under a sensor-homogeneous replication

Repeating the analysis on Suomi-NPP detections alone (see “Sensor-homogeneous replication”) reproduced every principal result almost exactly. The ONI–peat-fire-share correlation was unchanged to three decimal places (Pearson $r = 0.779$, $p = 0.0010$; Spearman $\rho = 0.829$, $p = 0.0003$), as was the leave-one-year-out range ($r = 0.744\text{--}0.850$, maximum $p = 0.0035$). The scaling exponent was 1.98 (95% CI $1.75\text{--}2.22$) with a tighter fit than the pooled record ($R^2 = 0.957$) and remained highly significantly steeper than unity ($p < 0.0001$), and the partial correlation controlling for fire-season magnitude was again indistinguishable from zero ($r = -0.03$, $p = 0.93$). The growth in the number of VIIRS platforms over the study period therefore does not account for any of the reported interannual relationships.

Spatial concentration of peat-fire emissions among recurring hotspots

Peat-classified fire detections occurred within 2,863 distinct 0.05° grid cells over the fourteen-year record (Fig. 5). The distribution of burn recurrence was strongly right-skewed: 551 cells (19.2%) recorded a peat fire in only one of the fourteen years, while 130 cells (4.5%) recorded a peat fire in eleven or more years (Table 2, Fig. 4). Cumulative FRP was substantially more concentrated than cell count: cells that burned in seven or more years (24.3% of all affected cells) accounted for 57.7% of cumulative FRP, whereas the 19.2% of cells that burned only once contributed just 2.1% of cumulative FRP. The single most persistent and intense location identified — a single 0.05° grid cell centred near 0.15°S , 109.35°E , in the coastal peatland of West Kalimantan — recorded a peat fire in all fourteen years, with 1,040 individual detections and a cumulative FRP of 6,535 MW. This one cell’s cumulative FRP exceeds that of every cell in the record that burned in only one of the fourteen years (the most intense one-time-burn cell reached 6,069 MW), even though it accounts for only 0.17% of the cumulative FRP summed across all 2,863 peat-fire-affected cells.

Table 2
Distribution of peat-fire recurrence and associated share of cumulative FRP across 2,863 affected 0.05° grid cells, 2012–2025.

Recurrence category (years burned, of 14)	Grid cells, n (%)	Share of cumulative FRP
1 (one-time)	551 (19.2%)	2.1%
2–4	1,049 (36.6%)	16.7%
5–6	566 (19.8%)	23.5%
7–14 (recurring)	697 (24.3%)	57.7%

No detectable change in ENSO sensitivity since the onset of national peatland restoration

Indonesia's Peatland Restoration Agency (Badan Restorasi Gambut, BRG) was established in January 2016 following the catastrophic 2015 fire season, with a target of rewetting, revegetating, and revitalizing 2 million hectares of degraded peatland by 2020; canal-blocking construction by BRG and its successor agency accelerated from 2017 onward (Castro et al., 2026). To provide an exploratory, descriptive test of whether the ENSO–peat-fire-share relationship has weakened since restoration efforts began, I compared the slope of peat-fire share on haze-season ONI before (2012–2015, $n = 4$) and after (2016–2025, $n = 10$) BRG's establishment. The fitted slope was nominally about twice as steep in the post-2016 period (17.5 percentage points of peat-fire share per unit ONI) as in the pre-2016 period (8.7 percentage points per unit ONI) — the opposite direction from what a restoration-effectiveness hypothesis would predict. However, when tested formally with an $\text{ONI} \times \text{period}$ interaction term in a pooled ordinary least-squares regression, this difference in slope was not statistically significant (interaction coefficient $p = 0.302$), and the pre-2016 sub-period contains only four years, giving this comparison very limited statistical power. I therefore report this result descriptively: this study finds no statistically detectable change in ENSO sensitivity associated with the onset of national restoration policy, but the analysis is materially underpowered to rule one out, and should not be read as evidence that restoration has been ineffective.

The ENSO–composition relationship weakens with proximity to the Sarawak border

Because `dist_to_sarawak_km` was computed for every fire detection during dataset construction, I additionally tested whether the ENSO–peat-fire-share relationship strengthens or weakens when the analysis is restricted to fires nearer the Sarawak border, which might be expected to be most directly relevant to transboundary haze. The relationship instead weakened monotonically with proximity: Pearson $r = 0.78$ ($p = 0.0010$) for the full domain, falling to $r = 0.56$ ($p = 0.037$) within 200 km of the border, $r = 0.38$ ($p = 0.182$, not significant) within 100 km, and $r = 0.28$ ($p = 0.331$, not significant) within 50 km. This pattern suggests that the ENSO-driven compositional shift documented here is primarily a landscape-scale phenomenon across the broader West/Central Kalimantan peatland expanse rather than one concentrated in fires immediately adjacent to the border, consistent with transboundary haze

reaching Sarawak predominantly via long-range smoke transport from the wider region rather than from a spatially narrow band of border-proximate fires.

A partially independent check using MODIS active-fire detections, 2001–2011

Repeating the peat-classification and ENSO-correlation procedure on MODIS Standard Product active-fire detections for 2001–2011 – the eleven fire seasons immediately preceding the start of the VIIRS record used for the principal analysis, and not pooled with the VIIRS-based series (see “Study area and data sources”) – yielded 323,711 classified MODIS fire detections, of which 86,576 (26.7%) fell on mapped peatland. The MODIS-only peat-fire share correlated positively with haze-season ONI (Pearson $r = 0.52$, $p = 0.102$, $n = 11$; Spearman $\rho = 0.58$, $p = 0.060$), the same direction as, but not reaching the same level of statistical significance as, the VIIRS-based 2012–2025 relationship. I read this as partial, qualitative corroboration rather than a full independent confirmation: beyond the reduced statistical power expected from the smaller sample (eleven versus fourteen years), MODIS's lower sensitivity to smouldering peat fires relative to VIIRS (see “MODIS-era robustness check”) offers a plausible further explanation for the weaker, noisier signal in this earlier period.

The scaling relationship survives transport to Sarawak, but the ENSO signal is attenuated

Across the eight fire seasons for which trajectories are available (2018–2025), the peat share of transport-weighted fire exposure at the twelve Sarawak receptors ranged from 1.9% (2020) to 26.6% (2019) and averaged 10.0% – systematically below the mean domain-wide peat-fire share over the same years (17.3%). Receptor-side composition tracked source-region composition closely ($r = 0.88$, $p = 0.0041$ against the domain-wide peat-fire share) and, as at the source, was better predicted by fire-season magnitude ($r = 0.83$, $p = 0.012$ against log total detections) than by ONI, against which the correlation was positive but not significant ($r = 0.44$, $p = 0.275$; Spearman $\rho = 0.62$, $p = 0.10$), compared with $r = 0.75$ ($p = 0.034$) for the domain-wide share over the same eight years. The super-linear scaling of the “Peat burning scales super-linearly with fire-season magnitude” section also survives transport: regressing log peat exposure on log total exposure gives an exponent of 1.59 (95% CI 1.03–2.14; $R^2 = 0.840$), significantly steeper than unity (one-sided $p = 0.042$) though shallower than the 1.96 obtained at the source. Smoke reaching Sarawak therefore does become disproportionately peat-derived as fire seasons intensify, but both the ENSO signal and the steepness of the scaling are attenuated relative to the source region – consistent with the weakening of the ENSO–composition relationship toward the border reported in the “The ENSO–composition relationship weakens with proximity to the Sarawak border” section, and with the eight-year trajectory record being considerably shorter than the fourteen-year fire record.

These receptor-side conclusions are not artefacts of the search radius or trajectory length. Across the twelve configurations tested (Table 3), the transport-weighted peat share averaged 7.5–10.0%, its correlation with the source-region peat-fire share remained strong throughout ($r = 0.69$ – 0.93), and its correlation with ONI failed to reach significance in every configuration ($r = 0.39$ – 0.51 , $p = 0.19$ – 0.34), confirming that the attenuation of the ENSO signal at the receptor is a property of the transport rather

than of the parameter choice. The scaling exponent ranged from 1.41 to 1.96 and exceeded unity significantly in ten of the twelve configurations; the two exceptions were the narrowest 50 km radius combined with the longer trajectories ($p = 0.067$ and 0.060), where the shrinking sample of attributable fires widens the confidence interval. The point estimate exceeded unity in all twelve.

The ongoing 2026 season: an out-of-sample observation

Restricted to 1 July–7 September and to Suomi-NPP alone, the 2026 season had already recorded 120,450 fire detections by 7 September, exceeding the previous maximum for this window – 92,498 in 2015 – by 30%, with more than seven weeks of the season still to run. Peat-fire detections reached 49,211, likewise exceeding the 2015 figure of 36,030 by 37%, and the peat-fire share stood at 40.9%, the second highest in the fifteen-year comparison after 2019 (45.9%). The season is developing under the strongest early-season El Niño in the ONI record: the May–July value reached + 1.39, above the + 1.19 of 2015 and the + 1.13 of 1997, and the highest for that season in the 1950–2026 series (NOAA Climate Prediction Center, 2026). Extending the scaling relationship of the “Peat burning scales super-linearly with fire-season magnitude” section to this window gives an exponent of 2.03 ($R^2 = 0.937$) over 2012–2025; the peat-fire count observed in 2026 falls within the prediction envelope of that relationship (standardised residual – 1.3), although below its central estimate. These figures carry an important qualification. The 2026 counts come from the NRT product whereas earlier years come from the Standard Product, and because NRT screening is less complete the margins quoted above are upper bounds rather than measured differences (see “The ongoing 2026 fire season”); the peat-fire share, being a ratio, is less exposed to this bias than the counts. The observation is therefore out-of-sample rather than a formal validation: the season is incomplete, the product differs, and a single season cannot test a relationship estimated from fourteen. Read with those caveats, the season now under way is among both the largest and the most peat-dominated in the record, which is the pattern the scaling relationship describes.

Discussion

Peat burning as a super-linear function of fire-season magnitude

The central quantitative result of this study is not that ENSO shifts fire composition – a claim these data cannot sustain independently of ENSO's effect on fire volume – but that peat burning scales super-linearly with fire-season magnitude, with an exponent close to two and an unusually tight fit ($R^2 = 0.89$ pooled, 0.96 for the sensor-homogeneous subset). Doubling the total number of fire detections in a season is accompanied by roughly a four-fold increase in peat-fire detections. A plausible physical reading is threshold-like: in quiet seasons the water table remains high enough that most peatland is simply not ignitable and fire is confined to drier mineral-soil and agricultural land, whereas as drought deepens an increasingly large fraction of the peat landscape crosses the moisture threshold below which smouldering can be sustained (Irfan et al., 2024), so that the peat-available area – and not merely ignition pressure – expands with fire-season severity. ENSO enters this picture as the dominant

upstream control on fire-season magnitude ($r = 0.79$ against log total detections), which is why El Niño years are also the peat-dominated years; the compositional shift follows from the scaling relationship rather than constituting a separate ENSO fingerprint. This distinction matters for interpretation: it means the peat fraction should be predictable from any indicator of seasonal fire severity, not only from ENSO indices, and that ENSO-based early warning is useful because ENSO forecasts fire-season magnitude, not because it carries independent information about composition.

The practical consequence is that the haze burden of a fire season grows considerably faster than its fire count. Because peat combustion releases substantially more particulate matter per unit of fuel consumed than flaming vegetation fires (Stockwell et al., 2016), and because the peat fraction itself rises with season size, particulate emissions scale with a steeper exponent than either quantity alone would imply. Fire counts, burned area and total FRP therefore systematically understate how much worse a large fire season is for air quality than a moderate one — a compounding that is invisible in metrics which do not separate peat from non-peat burning. This finding echoes, and adds a continuous quantitative dimension to, prior qualitative and single-event reports that peatland burning dominates the worst haze episodes (Field et al., 2016; Huijnen et al., 2016; Wooster et al., 2012). It is also complementary to Prasetyo et al.'s (2022) machine-learning analysis of Sumatran peat vulnerability, which classified 2012–2019 into discrete El Niño, La Niña, and Normal phases using the same ONI index to map where peat fire risk is highest under each phase (Prasetyo et al., 2022); the present study instead treats ONI as a continuous predictor and asks what fraction of all fires — rather than which locations are at risk — are attributable to peat, which to my knowledge has not previously been expressed as a continuous, testable statistical relationship at the interannual scale. A further exploratory check asked whether the share of cumulative peat-fire FRP contributed specifically by the recurrent hotspot cells identified in the “Spatial concentration of peat-fire emissions among recurring hotspots” section itself varies with ONI; the tendency was negative but statistically non-significant (Pearson $r = -0.34$, $p = 0.23$, $n = 14$), with the lowest hotspot-FRP share (45.6%) occurring in 2015, the strongest El Niño in the record. If real, this pattern would imply that El Niño-driven drought extends fire-affected peatland into marginal, non-recurrent cells rather than simply intensifying burning at the usual, already-degraded locations — a reading that lines up with Salmayenti et al.'s (2025) finding that the fire-hotspot advantage of drained over undrained peatland was itself weakest during the strong 2015 El Niño (Salmayenti et al., 2025); confirming this would require a longer record than attempted here.

Recurrence and implications for restoration prioritization

The concentration of cumulative FRP among a relatively small number of persistently recurring grid cells corroborates, rather than newly discovers, the central finding of Vetrita and Cochrane (2020), who used MODIS burned-area data (2001–2018) for all of Sumatra and Kalimantan and reported that 'almost half' of cumulative burned peatland area over that period was attributable to locations burning more than twice — a result strikingly similar in direction and rough magnitude to the 57.7% FRP share I attribute here to locations burning in half or more of the fourteen years examined (Vetrita & Cochrane, 2020). The present analysis differs methodologically in three respects: it uses VIIRS fire radiative power (an energy-

based, sub-daily metric) rather than MODIS burned area (an area-based, 500 m product); it defines recurrence at the level of individual calendar years within a fixed 0.05° grid rather than discrete burning events; and it is restricted to the West/Central Kalimantan–Sarawak border corridor most directly relevant to transboundary haze reaching Sarawak, together with a more recent and longer (2012–2025) record. My result should therefore be read as an independent replication, at finer spatial resolution and with an energy-based rather than area-based metric, of a pattern first quantified by Vetrina and Cochrane, and it aligns with a separate two-decade (2001–2021) burn-severity analysis of Kalimantan, which reported that the total peatland area burned fell by 28.7% on average in 2015–2021 relative to earlier periods even as the relative extent of 'high' and 'very high' severity burning rose by 12.1% and 13.4%, with 12% of that study region burning twice and roughly 23% burning more than twice over the two decades (Schmidt et al., 2024). This convergence across three independent studies, sensors, and metrics strengthens confidence that the underlying phenomenon — a small, identifiable subset of peatland locations driving a disproportionate share of cumulative fire emissions — is real rather than a methodological artefact of any one approach, even though the specific numerical concentration I report is not itself a new finding in isolation. A plausible structural explanation for why particular locations burn repeatedly is drainage infrastructure: Salmayenti et al. (2025) found that drained Sumatran and Kalimantan peatlands experienced up to thirteen times greater annual mean fire-hotspot density than undrained peatland of the same land-cover type, with the effect strongest in ENSO-neutral years and weakest during the strong 2015 El Niño, suggesting that canal proximity may predispose specific grid cells to recurrent ignition largely independent of ENSO phase (Salmayenti et al., 2025). The practical implication remains the same regardless of attribution of novelty: interventions at recurrent hotspots, such as the persistent location identified near 0.15°S, 109.35°E, would be expected to yield a disproportionate reduction in cumulative emissions relative to their small areal footprint, offering an evidence-based rationale for spatially targeted, rather than uniformly distributed, peatland rewetting and restoration investment.

Restoration policy and the spatial scale of ENSO sensitivity

That ENSO sensitivity shows no statistically detectable weakening since BRG's establishment (see “No detectable change in ENSO sensitivity since the onset of national peatland restoration”) does not, on its own, establish that peatland restoration in Kalimantan has failed. Castro et al. (2026) used a large-scale counterfactual (difference-in-differences) design over 3,840–3,992 canal blocks built by BRG and its successor agency in West and Central Kalimantan between 2017 and 2022 — the same provinces examined here — and found that canal blocks overlapping actively rewetted areas measurably reduced fire occurrence, with scaled-up best practice estimated to avoid up to 6.4% of burnt area (Castro et al., 2026). The contrast between that positive, spatially explicit finding and my null result is readily explained by differences in design: Castro et al. compared treated sites to matched, untreated counterfactual sites at fine spatial resolution, whereas my test compares only two highly aggregated time periods (with just four pre-2016 years) at the scale of the entire study domain. A landscape-average slope comparison of this kind is poorly suited to detecting effects that are concentrated at specific, well-managed restoration sites and diluted by continued degradation elsewhere; the null result fits just as comfortably with a

scenario in which restoration is locally effective but has not yet altered the aggregate, domain-wide relationship between ENSO and peat-fire share. A concrete illustration is the single most persistent hotspot identified in the “Spatial concentration of peat-fire emissions among recurring hotspots” section (0.15°S, 109.35°E), which recorded a peat fire in every one of the fourteen years examined – including every year since BRG's establishment, without exception – a stark reminder, at the level of one well-documented recurrent location, that the domain-wide null result is not merely a statistical artefact of aggregation; whether this particular site had in fact been targeted for canal-blocking cannot be determined from the present data. This interpretation is further supported by a hydrological-modelling study of rewetting in Riau, Sumatra, which found that large-scale rewetting roughly halved the frequency of extreme fire events (from seven to four events, 2015–2021) and modestly reduced the area affected, yet widespread, prolonged extreme fire hazard still occurred in the strong El Niño years of 2015 and 2019 despite rewetting – indicating that restoration measurably lowers baseline fire hazard without fully offsetting landscape-scale ENSO forcing (Taufik et al., 2023). Ecosystem-level recovery after fire is also gradual rather than immediate: a sixteen-year tracking study of a Kalimantan peat forest found that burned areas showed only partial recovery of tree cover and biodiversity within twelve years and remained vulnerable to reversal by repeated fire, implying that restoration benefits may accrue over a longer timescale than the ten post-2016 years available for my comparison (Harrison et al., 2024). The distance-gradient result (see “The ENSO–composition relationship weakens with proximity to the Sarawak border”) is, to my knowledge, a novel observation for this specific ENSO–composition relationship and is broadly consistent with single-event case studies elsewhere in the region – for example, Putra et al. (2021) reported a peat-to-non-peat hotspot ratio of roughly 4:1 during the 2019 fire season in South Sumatra, a landscape-scale rather than border-proximate pattern (Putra et al., 2021) – and reinforces that transboundary haze management strategies should target the broader peatland landscape rather than assuming risk is concentrated immediately at the frontier.

Implications for the 2026 crisis and for anticipating the next one

The 2026 season, unfolding as this manuscript was written, illustrates why the distinction drawn here matters operationally. By 7 September it had already exceeded every previous season in the record for the equivalent window – by a margin that the near-real-time product makes an upper bound rather than an exact figure – with the peat-fire share at 40.9% and more than seven weeks remaining (see “The ongoing 2026 season”). If the scaling relationship holds, the implication for a season of this size is not simply more fire but disproportionately more peat fire, and therefore a particulate burden that grows faster still. Response capacity that is planned against expected fire counts, burned area or total radiative power will be sized to the wrong quantity, because none of those metrics carries the compositional shift that governs smoke production.

Three practical consequences follow. First, the peat fraction is forecastable in advance of the season, because it is predicted by fire-season magnitude, which ENSO in turn governs; the May–July ONI of +1.39 in 2026 was already the highest in the ONI record before the worst of the burning began. Seasonal fire-risk systems that trigger anticipatory action have been shown to reduce peat fire incidence where

they are linked to preparedness and resources (Kieft et al. 2026), and the scaling relationship supplies a quantitative basis for setting the severity of that response. Second, because a small number of recurrently burning locations contribute a disproportionate share of cumulative emissions (see “Spatial concentration of peat-fire emissions among recurring hotspots”), suppression and rewetting effort directed at those locations should yield returns out of proportion to their area — and the single most persistent location identified here has burned in every year of the record, including every year since the national restoration programme began. Third, the attenuation of the ENSO signal but persistence of the scaling relationship at the Sarawak receptors (see “The scaling relationship survives transport to Sarawak”) indicates that the haze reaching Malaysia is governed by the aggregate size of the Kalimantan fire season rather than by conditions near the border, so bilateral measures confined to the frontier are unlikely to be sufficient.

None of this is a forecast of how the 2026 season will end, and the analysis presented here cannot make one. What it offers is a quantified expectation of how the peat fraction — and hence the haze burden — scales as a season intensifies, which is the quantity that preparedness has to be sized against.

Limitations

Several limitations should be considered when interpreting these results. First, although the leave-one-year-out sensitivity analysis (see “Statistical analysis of the ENSO–peat-fire-share relationship”) indicates that the relationship is not driven by any single influential year, the annual-level ENSO analysis is nonetheless based on a modest number of independent years ($n = 14$); a longer observational record would allow more robust trend estimation and the use of formal time-series or panel-regression methods, and would help clarify whether the relationship is genuinely linear or, as some individual years (e.g., 2019 versus 2023) hint, better described by a threshold or saturating response. The MODIS-era check (see “A partially independent check using MODIS active-fire detections”) partially addresses this concern by extending the observed direction of the relationship back a further eleven years, but its weaker, non-significant correlation ($r = 0.52$, $p = 0.102$) means it should be read as corroborating evidence for the sign of the relationship rather than as adding statistical power to the primary fourteen-year estimate, and I did not pool it into a single 25-year regression precisely because MODIS and VIIRS are not equally sensitive to the smouldering peat fires that drive the effect of interest. Second, the pooled fire-detection record is not sensor-homogeneous: one VIIRS platform was in orbit for 2012–2017, two from 2018 and three from 2024, which inflates absolute counts independently of fire activity. This concern is directly addressed rather than merely acknowledged — every interannual result was recomputed on the Suomi-NPP-only subset, which is homogeneous across all fourteen years, and reproduced almost exactly (see “The interannual results are unchanged under a sensor-homogeneous replication”) — so the growth in platform count can be excluded as an explanation for the reported relationships. The absolute detection counts in Table 1 nonetheless remain non-comparable across sub-periods and should not be read as a fire-activity time series. Third, PEATMAP is a global compilation product and its spatial resolution and currency may not capture fine-scale or recent peatland boundary changes as accurately as a dedicated national peat map would; misclassification near peatland margins

would tend to bias the peat-fire share toward the mean and could cause my reported relationship to be a conservative (under-)estimate. Fourth, VIIRS 375 m active-fire detection has a minimum detectable fire size and is subject to cloud and canopy obscuration, so the detection counts used here are an index of, rather than a census of, actual fire occurrence. Fifth, the 0.05° grid resolution used for the recurrence analysis is a methodological choice; results at markedly finer or coarser resolutions could shift the specific percentages reported, though the qualitative pattern of concentration is expected to be robust given both its consistency across recurrence categories tested here and its convergence with the independently derived, area-based estimate of Vetruta and Cochrane (2020) (Vetruta & Cochrane, 2020). Finally, this analysis is observational and correlational; it does not by itself establish the physical mechanism linking ONI to peat-fire prevalence, although that mechanism — ENSO-driven drought lowering the peat water table — is independently documented by ground-based groundwater monitoring (Irfan et al., 2024).

Conclusion

Using fourteen years of harmonised satellite fire detections classified against a peatland map, this study shows that peat burning in the West Kalimantan–Sarawak border region scales super-linearly with fire-season magnitude, with a power-law exponent close to two: a doubling of total fire activity is accompanied by roughly a four-fold rise in peat burning. This scaling is tight ($R^2 = 0.89$, rising to 0.96 on a sensor-homogeneous subset), stable under leave-one-year-out re-estimation, and survives transport to Sarawak receptors with a shallower but still super-linear exponent of 1.59. It also explains why El Niño years are peat-dominated: ENSO governs fire-season magnitude, and the peat fraction follows. I could not, by contrast, establish that ENSO acts on fire composition independently of fire-season magnitude — the two are too strongly collinear over fourteen years to separate — and I therefore do not claim such an effect. It further shows that a small fraction of peatland locations that burn repeatedly account for a disproportionate share of cumulative fire radiative power, a finding that independently corroborates, using VIIRS FRP at finer spatial resolution and over a more recent period, the area-based result reported by Vetruta and Cochrane (2020) for Sumatra and Kalimantan as a whole. Two further exploratory tests add texture: I find no statistically detectable change in ENSO sensitivity since the 2016 onset of national peatland restoration policy, a likely underpowered test whose null result is best read alongside the finer-resolution causal evidence discussed in the “Restoration policy and the spatial scale of ENSO sensitivity” section, rather than as a verdict on restoration effectiveness in its own right; and I find that the ENSO–composition relationship weakens closer to the Sarawak border, indicating that it is primarily a landscape-scale phenomenon rather than one concentrated at the frontier. A sensor-independent check using MODIS detections for 2001–2011 reproduces the same positive ENSO–peat-fire-share relationship found in the primary VIIRS record, though more weakly and without reaching significance, offering partial rather than full corroboration of its persistence over a longer, 25-year window. Together, these findings refine previously qualitative or coarser-resolution understanding of the Kalimantan fire regime into testable quantitative relationships and provide a concrete, spatially explicit basis for prioritizing ENSO-informed early warning — consistent with recent evidence that seasonal fire-risk prediction systems

linked to anticipatory action can measurably reduce peat fire incidence (Kieft et al., 2026) – and targeted peatland restoration.

Declarations

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Author contributions. T.T. designed the study, assembled and processed the data, performed all analyses, prepared the figures and wrote the manuscript.

Data availability. The derived datasets that support the findings of this study are openly available in Zenodo at <https://doi.org/10.5281/zenodo.23251423> (version 1.0.0). The deposit contains the peat-classified fire-level dataset, the year-level summaries underlying Tables 1 and 2 and Figures 1–5, the peat-fire recurrence grid, the transport-weighted exposure dataset for the Sarawak receptors and the trajectory sensitivity analysis reported in Table 3. All primary data are publicly available from their original providers and are not redistributed in the deposit: active-fire detections from the NASA FIRMS Area API (VIIRS 375 m and MODIS Standard Products; <https://firms.modaps.eosdis.nasa.gov/>); peatland extent from PEATMAP (Xu et al., 2018); the Oceanic Niño Index from the NOAA Climate Prediction Center (https://origin.cpc.ncep.noaa.gov/products/analysis_monitoring/ensostuff/ONI_v5.php); administrative boundaries from GADM version 4.1 (<https://gadm.org/>); and the meteorological fields driving the trajectory calculations from the NOAA ARL GDAS archive (<https://www.ready.noaa.gov/archives.php>).

Code availability. The Python and JavaScript code used to download and classify the data, to perform all analyses and to generate the figures and tables is included in the same Zenodo deposit (<https://doi.org/10.5281/zenodo.23251423>, version 1.0.0). It includes the verification script that recomputes every numerical value reported in this manuscript from the deposited datasets.

Use of AI tools. An AI assistant (Anthropic Claude) was used to draft and revise the analysis scripts and the manuscript text, as documented in the “Software, statistical conventions and use of AI tools” section. The author reviewed and verified all analyses, results and text, and takes full responsibility for the content of this manuscript.

Ethical responsibilities of authors. All authors have read, understood, and have complied as applicable with the statement on "Ethical responsibilities of Authors" as found in the Instructions for Authors.

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Figures

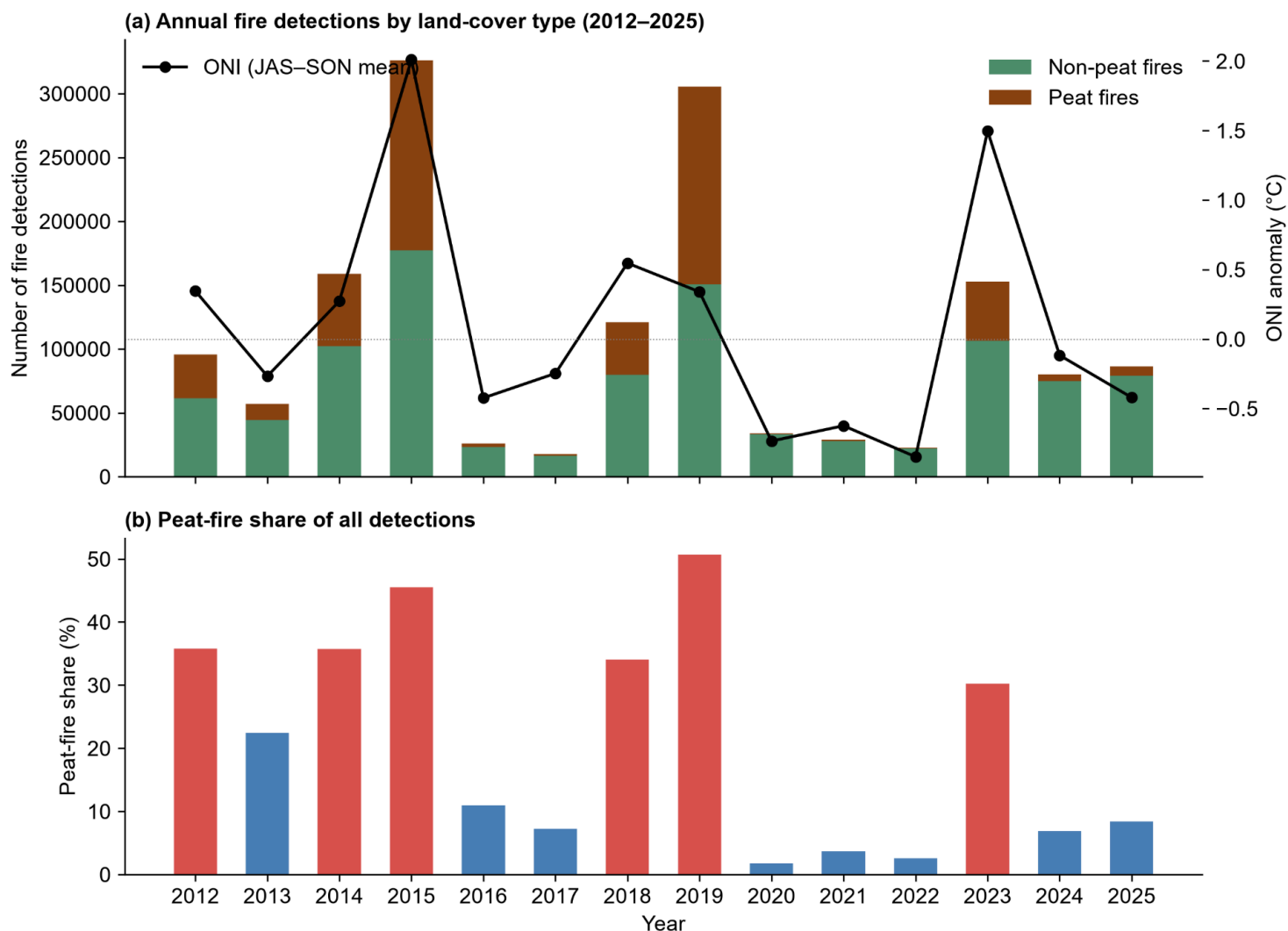


Figure 1

(a) Annual fire detections by land-cover type (peat vs. non-peat), 2012–2025, with the haze-season ONI overlaid. Detections come from one VIIRS platform in 2012–2017, two from 2018 and three from 2024 (see “Study area and data sources”). (b) Peat-fire share of all detections by year, coloured by ENSO sign (red = positive ONI, blue = negative ONI)

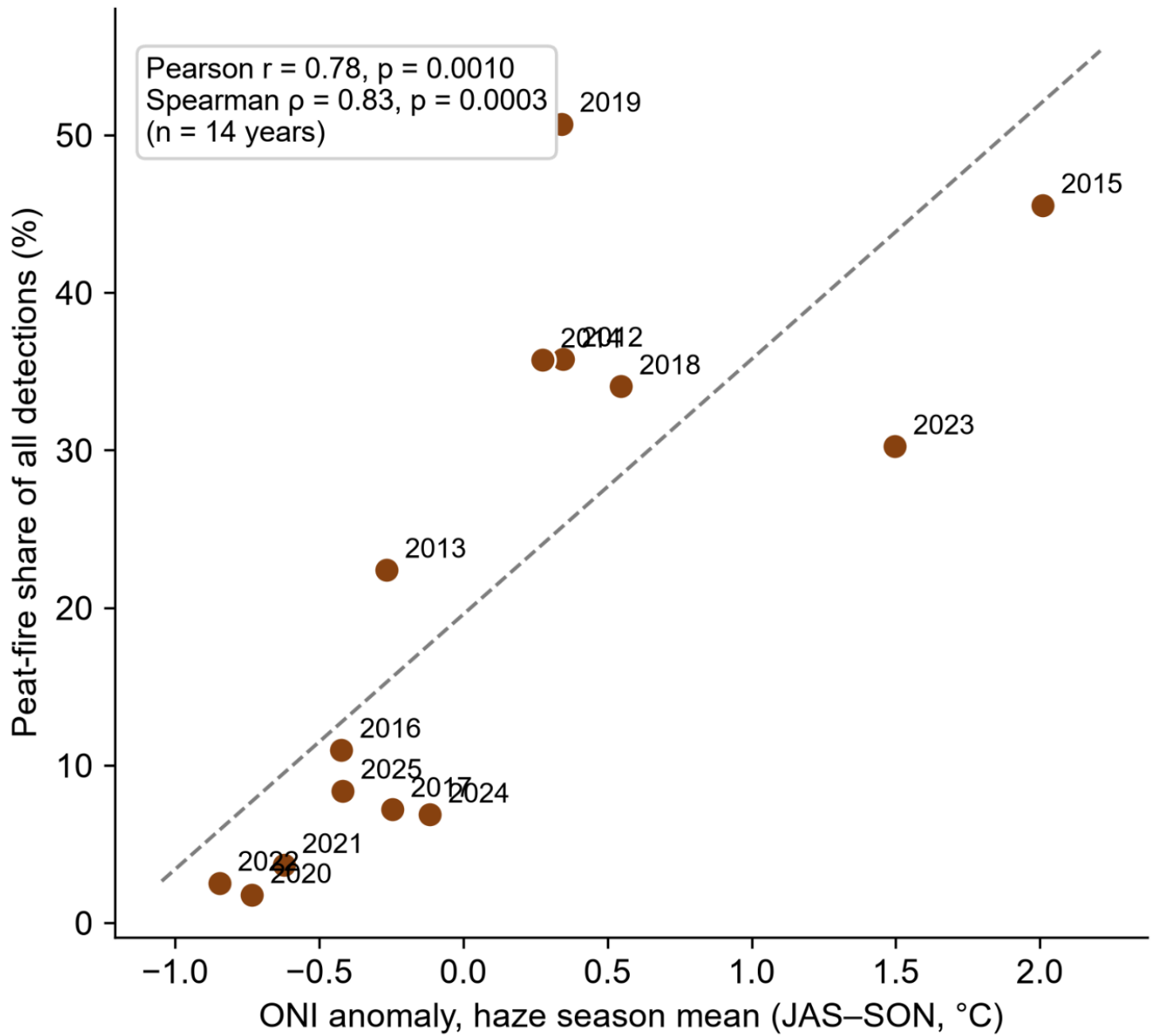


Figure 2

Relationship between haze-season ONI and peat-fire share, 2012–2025 ($n = 14$ years). Dashed line: ordinary least-squares fit

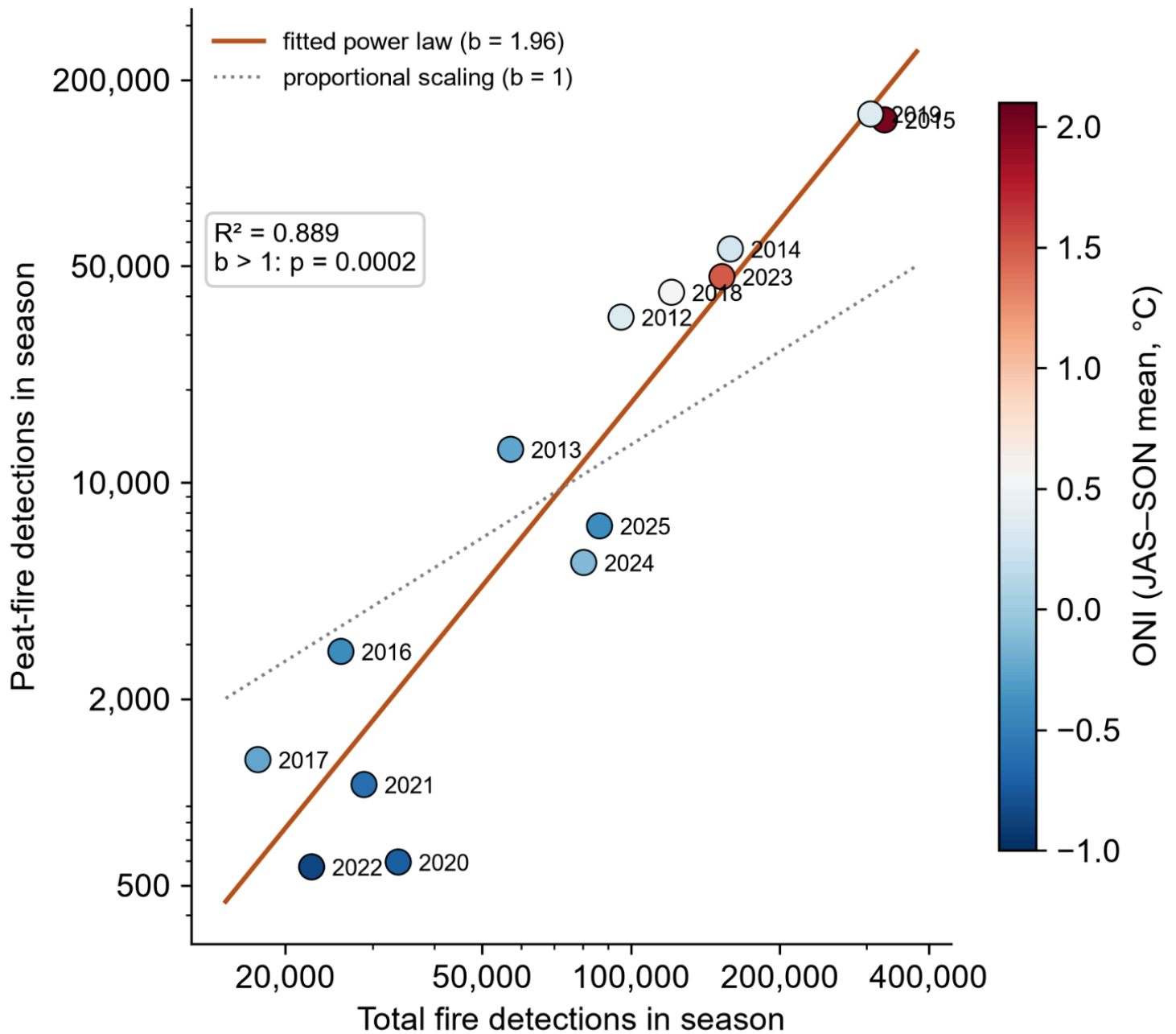


Figure 3

Super-linear scaling of peat burning with fire-season magnitude, 2012–2025, on logarithmic axes. Each point is one fire season, coloured by haze-season ONI. The fitted power law (orange) has exponent $b = 1.96$; the dotted grey line shows proportional scaling ($b = 1$) anchored at the geometric mean of the data

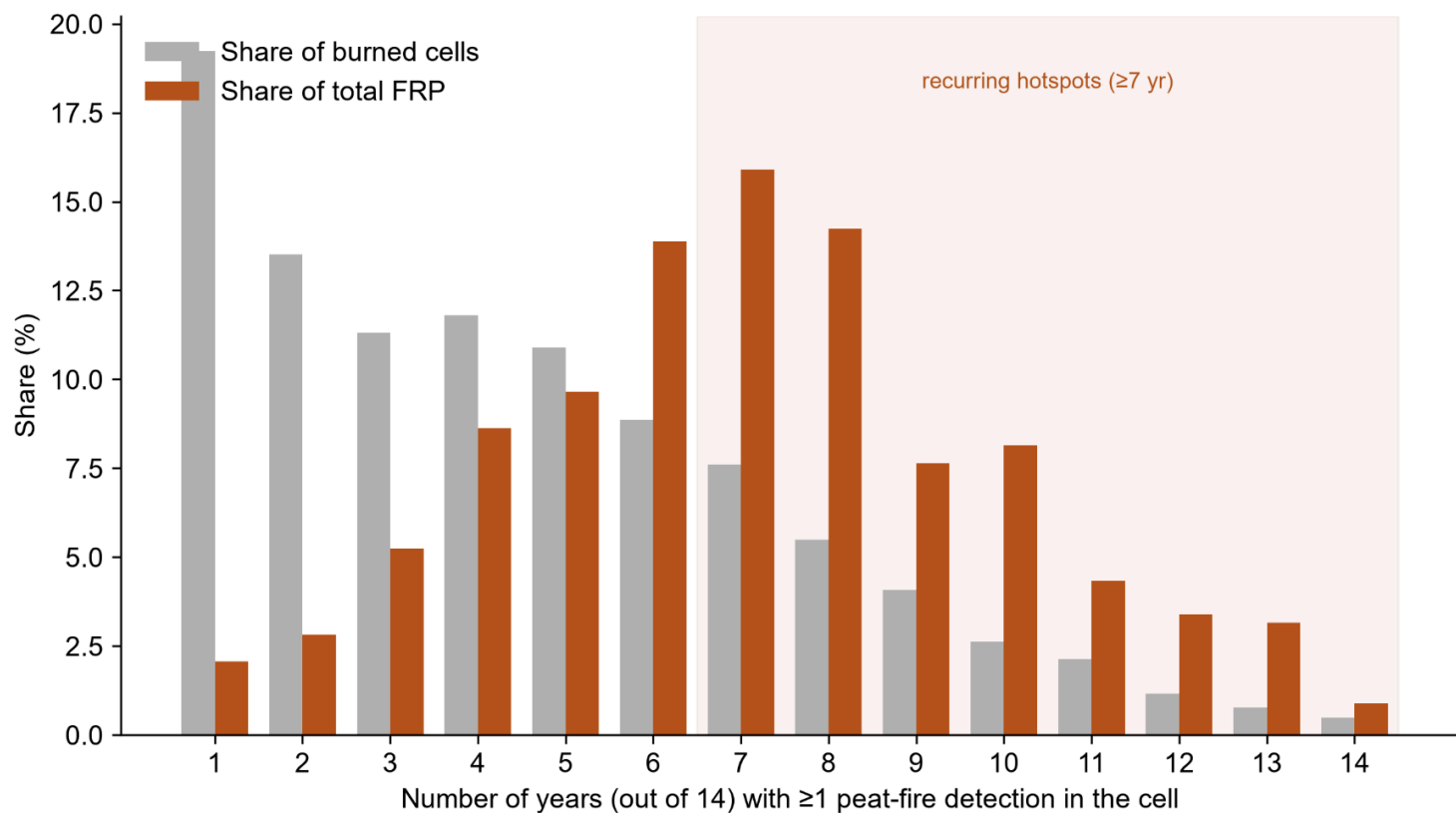


Figure 4

Share of peat-fire-affected grid cells (grey) and share of cumulative fire radiative power (orange) by number of years burned out of fourteen. Shaded region indicates recurring hotspots (≥7 years)

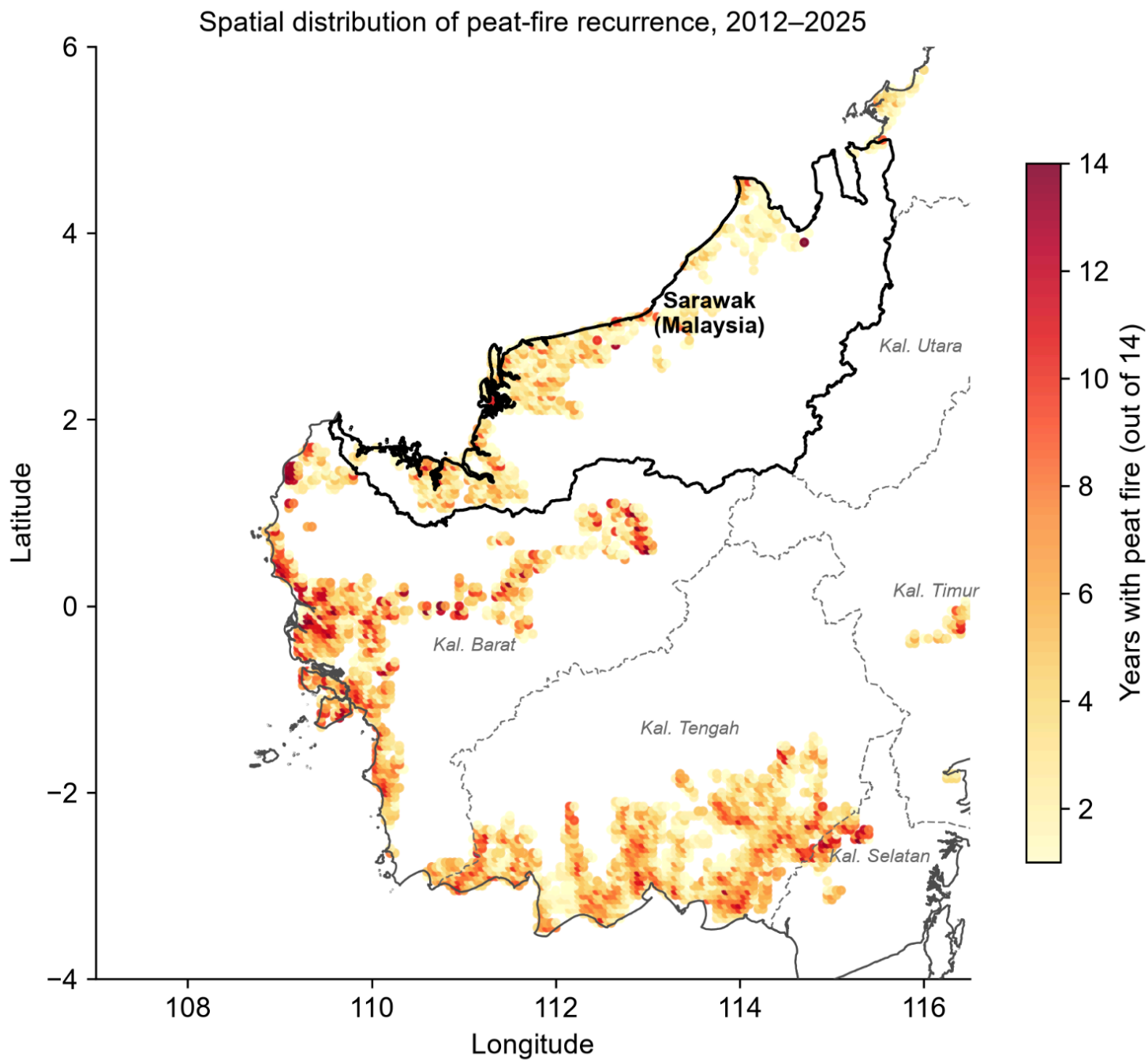


Figure 5

Share of peat-fire-affected grid cells (grey) and share of cumulative fire radiative power (orange) by number of years burned out of fourteen. Shaded region indicates recurring hotspots (≥ 7 years)