

# Reconstructing candidate active-fire events in a tropical peatland landscape using radar corroboration, robustness analysis and independent optical audit

Mahturai Rian Fitra<sup>1\*</sup>, Rujito Agus Suwignyo<sup>2</sup>, Dinar Dwi Anugerah Putranto<sup>3</sup>,  
Wijaya Mardiansyah<sup>4</sup>

<sup>1</sup> Doctoral Program in Environmental Science, Graduate School, Universitas Sriwijaya, Jl. Padang Selasa No. 524, Bukit Besar, Palembang 30139, South Sumatra, Indonesia

<sup>2</sup> Agronomy Study Program, Faculty of Agriculture, Universitas Sriwijaya, Jl. Raya Palembang-Prabumulih Km. 32, Indralaya, Ogan Ilir 30662, South Sumatra, Indonesia

<sup>3</sup> Master's Program in Civil Engineering, Faculty of Engineering, Universitas Sriwijaya, Jl. Raya Palembang-Prabumulih Km. 32, Indralaya, Ogan Ilir 30662, South Sumatra, Indonesia

<sup>4</sup> Physics Study Program, Faculty of Mathematics and Natural Sciences, Universitas Sriwijaya, Jl. Raya Palembang-Prabumulih Km. 32, Indralaya, Ogan Ilir 30662, South Sumatra, Indonesia

\* Corresponding author's e-mail: rianmahturai@gmail.com

## ABSTRACT

Satellite active-fire products can repeatedly sample the same fire episode across sensors and overpasses, creating pseudo-replication and uncertain event-level labels. We developed an auditable workflow to reconstruct candidate fire events in the Tanjung Lago-Banyuasin II tropical peatland landscape, quantify Sentinel-1 corroborative support, and conduct an independent Landsat 8/9 optical audit while preserving unresolved evidence. MODIS and VIIRS detections were harmonized, confidence-filtered, and linked using prespecified pairwise limits of 1 km and 24 h. Of 437 harmonized detections, 415 were retained and reconstructed into 218 candidate events. A Sentinel-1 decision rule was developed on 18 clusters, frozen before evaluation, and applied unchanged to a stratified random sample of 60 clusters. Following robustness and leave-one-acquisition-out analyses, 15 events were provisionally corroborated, 24 partially corroborated, and 21 unresolved; 56 of 60 primary decisions were stable. The design-weighted estimated proportion with at least partial radar support was 57.58% (95% CI 44.41–70.76%). An independently specified Landsat 8/9 audit, with thresholds frozen before unblinding, identified seven REF-FIRE events, all within the Sentinel-1-supported group; no event met the conservative REF-NOFIRE criteria, and most optical outcomes remained unresolved because imagery was insufficient or inconclusive. The framework reduces repeated counting while keeping detection provenance, corroborative evidence, and downstream label eligibility distinct. It is intended for auditable event reconstruction and label governance rather than fire-detection or burned-area accuracy assessment.

**Keywords:** tropical peatland, active fire, candidate event reconstruction, radar corroboration, optical audit, label governance.

## INTRODUCTION

Peatland fires in Indonesia impose substantial greenhouse-gas, biodiversity, ecosystem, and public-health costs. Fire-related PM<sub>2.5</sub> exposure has been estimated to contribute to approximately 33,100 premature adult deaths and 2900 infant

deaths annually (Hein et al., 2022). In coastal and deltaic peatlands, drainage and land conversion disrupt hydrological integrity and lower water tables (Ismail et al., 2021; Taufik et al., 2022). Access, landscape change, and governance conditions further shape fire susceptibility and persistence (Horton et al., 2021; Page et al., 2022).

Recent studies also emphasize institutional and landscape-scale controls on peat-fire risk (Abdurrahim et al., 2026; Sutikno et al., 2026).

Historical active-fire archives are valuable for reconstructing fire activity, but individual detections are not equivalent to independent fire events. Repeated observations across sensors and overpasses can create pseudo-replication, whereas overly permissive linking rules can merge distinct episodes (Balch et al., 2020; Bernini et al., 2026). Defensible event reconstruction therefore requires explicit spatiotemporal rules, stable event identifiers, and transparent sensitivity analysis, particularly in multi-source archives (Deng et al., 2026).

MODIS and VIIRS locate thermal anomalies rather than burned-area boundaries or independent event-level reference labels. Detection varies with sensor characteristics, fire intensity, atmospheric conditions, and viewing geometry (Fu et al., 2020; Briones-Herrera et al., 2020). Product-specific algorithms and sensor characteristics also influence which thermal anomalies are retained (Schroeder et al., 2014; Giglio et al., 2016). Cross-product agreement was therefore retained as provenance rather than treated as confirmation of fire occurrence.

Existing approaches address individual components of this problem. Event separation and fire-event delineation have been addressed through explicit temporal and spatial rules (Oom et al., 2016; Balch et al., 2020). Multi-sensor aggregation and reference-data construction introduce additional challenges for evidence governance (Briones-Herrera et al., 2020; Franquesa et al., 2020). Reference-data uncertainty further depends on analyst and evidence quality (Franquesa et al., 2022). Yet few workflows integrate event reconstruction, sensor-specific provenance, pre-evaluation rule freezing, independent optical auditing, and explicit downstream label governance within a single traceable framework, particularly for tropical peatlands. This leaves a governance gap in converting multi-sensor active-fire detections into auditable candidate-event labels while preserving unresolved evidence and avoiding forced binary classification.

This study developed an auditable, uncertainty-aware workflow that integrates detection provenance, graph-based event reconstruction and chain-effect auditing, quantitative Sentinel-1 corroboration, an independent Landsat 8/9 audit, and explicit downstream label governance. Sentinel-1 rules were developed and frozen before application

to the held-out Evaluation60 sample, while ambiguous radar or optical evidence was retained as uncertainty rather than forced into binary labels.

The objectives were to reconstruct candidate events from harmonized MODIS/VIIRS detections; test sensitivity to linking assumptions and chain effects; derive frozen Sentinel-1 evidence-support states and downstream eligibility classes; assess decision stability; and independently audit Evaluation60 with Landsat 8/9. The study therefore addresses candidate-event reconstruction, corroborative evidence, and label eligibility rather than burned-area mapping or field-reference accuracy.

## MATERIALS AND METHODS

### Study area and analysis period

The study covered a 142.35 km<sup>2</sup> peatland landscape in Tanjung Lago–Banyuasin II, lower Musi Delta, South Sumatra, Indonesia, corresponding to BBSDLP peat polygon GID 155. The polygon is mapped as D2 peat (100 to <200 cm) and dominated by Hemic Organosols over clay deposits; this mapped class was not treated as field-validated depth at individual events. Metric analyses used UTM Zone 48S (EPSG:32748), and mapped landscape features were retained for spatial context rather than event linking.

The archive spanned 22 February 2015 to 29 October 2025. Because 2015 and 2025 were incomplete, monthly and annual counts were descriptive rather than standardized rates. Cluster month was assigned from *t*<sub>0</sub>, the UTC timestamp of the first retained active-fire detection.

### Data sources and processing platforms

The active-fire archive comprised MODIS Collection 6.1, VIIRS NOAA-20 Collection 2, and VIIRS Suomi-NPP Collection 2 detections obtained from NASA FIRMS (NASA Earthdata, n.d.; NASA FIRMS, n.d.). The product algorithms and sensor characteristics are documented by Schroeder et al. (2014) and Giglio et al. (2016). Sentinel-1 GRD IW VV/VH imagery provided the radar evidence stream, Landsat 8/9 Collection 2 Level-2 imagery supported the independent optical audit, and the peat boundary came from BBSDLP (2019). The 2025 land-cover backdrop in Figure 1 used the Esri/Impact Observatory Sentinel-2 10-m annual land-cover time series

(Karra et al., 2021). Sentinel-1 responses were interpreted as empirical C-band surface/structural evidence rather than direct fire truth, consistent with peatland backscatter studies showing sensitivity to wetness and surface conditions (Millard et al., 2022). The 1-km grid and other mapped landscape features were used only for spatial auditing or cartographic context and did not enter event linking or evidence classification.

QGIS 3.22.10 supported spatial inspection and cartography, Google Earth Engine processed Sentinel-1 and Landsat imagery, and Python implemented harmonization, graph reconstruction, sensitivity/robustness analyses, deterministic classification, weighted estimation, and quality control. GEE served as the image-processing environment, while final analytical logic and verification were implemented outside the browser.

### Active-fire harmonization and confidence filtering

The 437 detections were harmonized into a common multi-sensor structure containing coordinates, acquisition time, sensor/product,

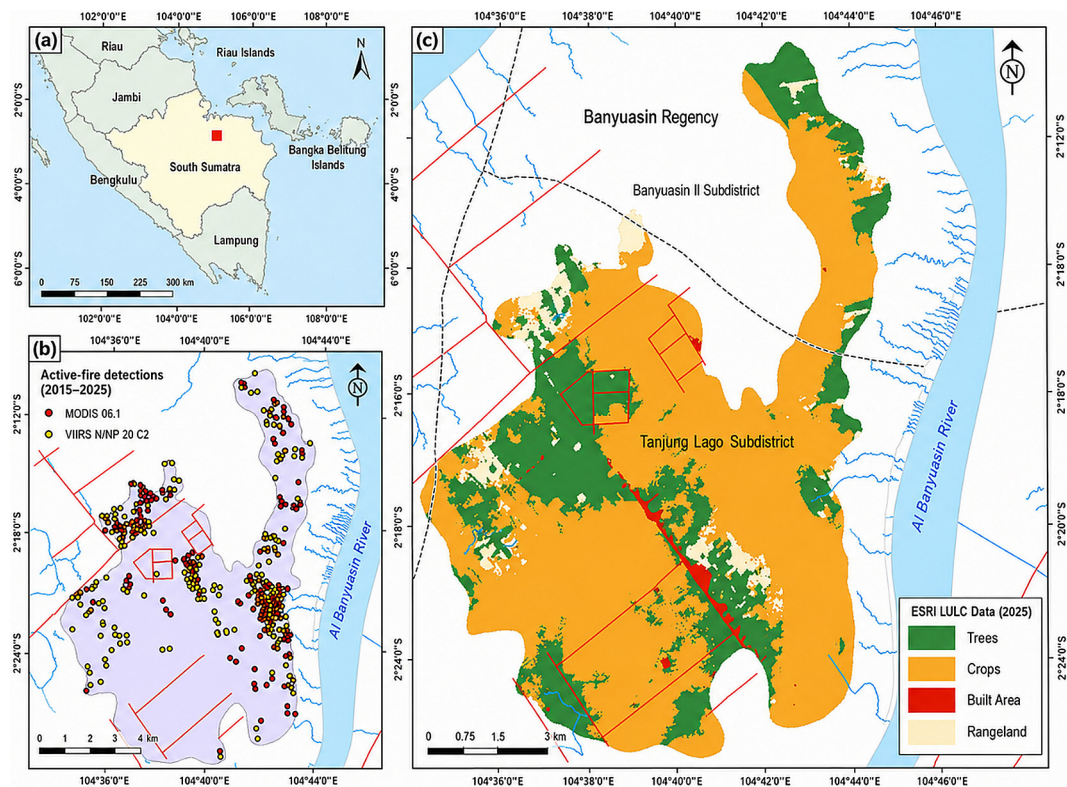
confidence, FRP, day/night status, and stable detection identifiers (Bernini et al., 2026). Coordinates were transformed to EPSG:32748 for metric operations while geographic coordinates were retained for provenance.

Confidence filtering was applied before clustering. MODIS detections with confidence  $\geq 30$  and VIIRS nominal/high detections were retained; 415 detections passed and 22 low-confidence records were excluded. This confidence rule was treated as an operational screening criterion rather than a universal fire-validity threshold (Shofiana and Sitanggang, 2021). A high-confidence-only subset was retained only as a restrictive sensitivity scenario (Tables 1–2).

The post-filter workflow, including frozen-rule development, held-out evaluation, robustness analysis, Landsat corroboration, and weighted inference, is summarized in Figure 2.

### Graph-based spatiotemporal clustering

Each retained detection was a graph node. Nodes were linked when separated by  $\leq 1.000$  m and  $\leq 24$  h in actual UTC time, and each connected



**Figure 1.** Tanjung Lago-Banyuasin II peatland landscape: (a) regional location; (b) confidence-filtered MODIS/VIIRS active-fire detections during 2015–2025; and (c) 2025 Esri/Impact Observatory Sentinel-2 10-m land-cover context (Karra et al., 2021), with ancillary hydrography, canals, roads, and administrative boundaries shown for cartographic orientation only

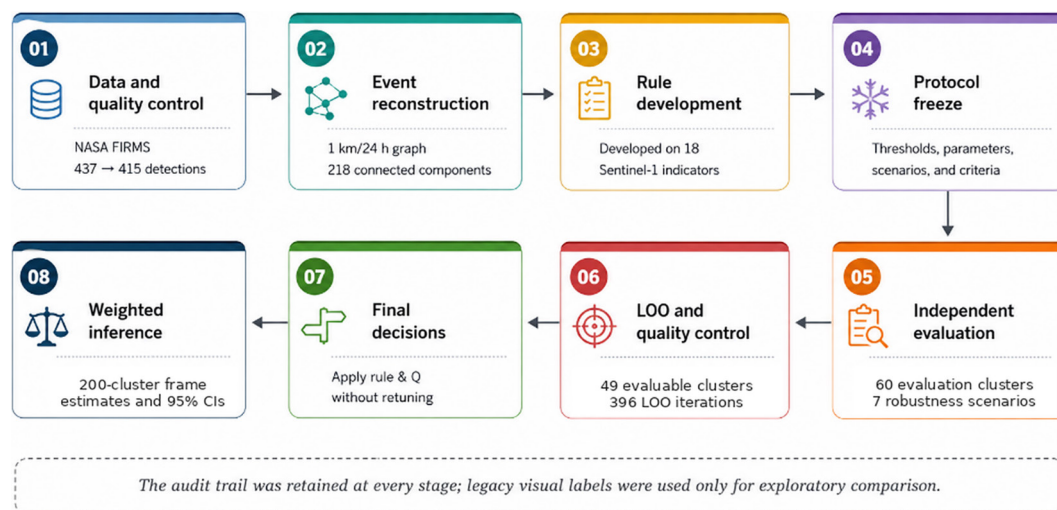
**Table 1.** Active-fire products, sensor platforms, initial detection counts, and roles in candidate-event inventory construction

| Product          | Sensor | Platform       | Initial n | Role in candidate inventory                          |
|------------------|--------|----------------|-----------|------------------------------------------------------|
| VIIRS NOAA-20 C2 | VIIRS  | NOAA-20/JPSS-1 | 80        | Primary active-fire source                           |
| MODIS C6.1       | MODIS  | Terra/Aqua     | 50        | Historical complement; coarser-resolution comparator |
| VIIRS S-NPP C2   | VIIRS  | Suomi NPP      | 307       | VIIRS complement and temporal support                |

**Table 2.** Product-specific outcomes of confidence filtering for active-fire detections

| Product          | Init. n | Ret. n | Excl. n | L  | N   | H  | Retention |
|------------------|---------|--------|---------|----|-----|----|-----------|
| MODIS C6.1       | 50      | 48     | 2       | 2  | 37  | 11 | 96.0%     |
| VIIRS NOAA-20 C2 | 80      | 77     | 3       | 3  | 77  | 0  | 96.2%     |
| VIIRS S-NPP C2   | 307     | 290    | 17      | 17 | 287 | 3  | 94.5%     |
| Total            | 437     | 415    | 22      | 22 | 401 | 14 | 95.0%     |

**Note:** L – low confidence; N – nominal confidence; H – high confidence.



**Figure 2.** Core Sentinel-1 workflow separating rule development (Development18) from evaluation (Evaluation60), freezing parameters before application, and testing P-PP-U/A-D decisions through seven scenarios, LOO analysis, and weighted estimation. The independent Landsat audit was conducted separately after this radar protocol had been frozen

component defined a candidate event, consistent with explicit event-individuation approaches (Oom et al., 2016; Balch et al., 2020). Recent multi-source event-reconstruction frameworks likewise emphasize transparent spatiotemporal linkage rules (Bernini et al., 2026; Deng et al., 2026). Stable cluster identifiers were assigned after deterministic sorting, and transitive chain effects were explicitly flagged when overall event extent or duration exceeded pairwise thresholds even though every graph edge satisfied the linking rule.

Complete detection-to-event lineage was archived in machine-readable form for all 415 retained detections. Each unique retained detection

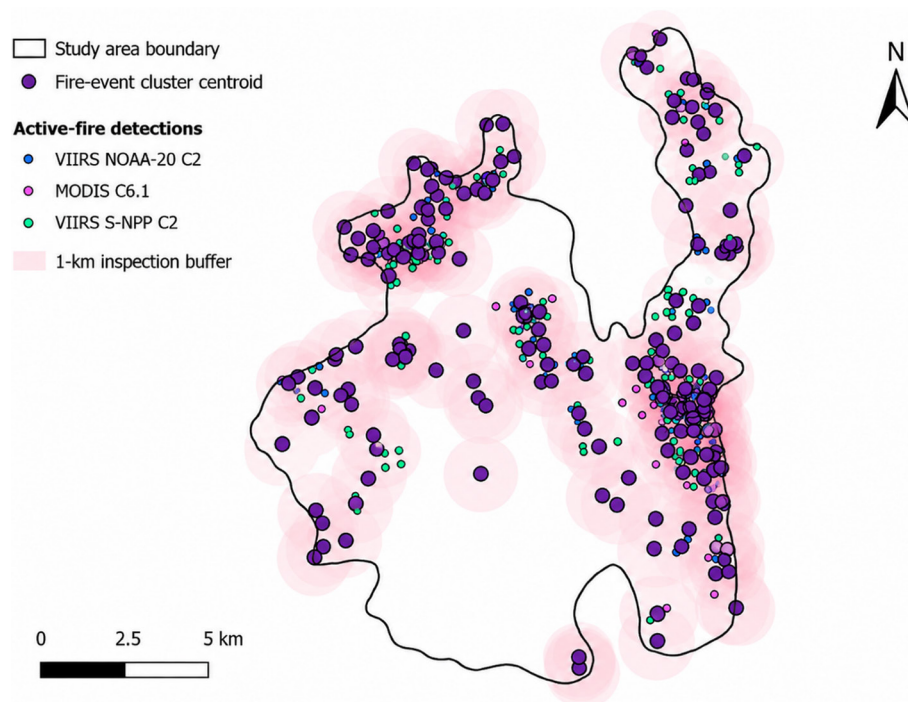
identifier was linked to one reconstructed candidate-event identifier together with detection attributes, event attributes, audit partition, and downstream P/PP/U and A-D classifications where such classifications were available from the prespecified audit partitions. Cross-file verification confirmed 415 unique detection identifiers mapped to 218 unique events without duplicated or unassigned retained detections, and the event-level hotspot counts summed to 415 (Supplementary Table S10 and accompanying machine-readable lineage table).

Each event retained centroid, time range, duration, hotspot count, source-product count, FRP

**Table 3.** Threshold sensitivity of graph-based event reconstruction

| Scenario               | d (m) | t (h) | n   | MP | SP  | S   |
|------------------------|-------|-------|-----|----|-----|-----|
| Conservative spatial   | 500   | 24    | 266 | 29 | 237 | 195 |
| Conservative temporal  | 1,000 | 12    | 244 | 32 | 212 | 169 |
| Main                   | 1,000 | 24    | 218 | 34 | 184 | 139 |
| Temporal relaxation I  | 1,000 | 48    | 187 | 36 | 151 | 116 |
| Temporal relaxation II | 1,000 | 72    | 174 | 39 | 135 | 102 |
| Spatial relaxation     | 2,000 | 24    | 197 | 39 | 158 | 115 |

**Note:** d – spatial linkage limit; t – temporal linkage limit; n – reconstructed candidate-event count; MP – multi-product; SP – single-product; S – singleton.



**Figure 3.** Active-fire detections, centroids of 218 candidates from the 1-km/24-h rule, and the 1-km exclusion zone. Buffers support auditing and control screening, not burned-area delineation. Singletons are a subset of single-product clusters. Detailed buffer sensitivity is reported in Table S4

summaries, spatial extent, provenance class (multi-product, single-product non-singleton, or singleton), chain-effect diagnostics, and audit-partition/downstream-label fields where available.

### Threshold and buffer sensitivity analysis

The primary 1-km/24-h rule was compared with five alternatives: 500-m/24-h, 1-km/12-h, 1-km/48-h, 1-km/72-h, and 2-km/24-h. Event count, provenance composition, singleton fraction, duration, and spatial extent were compared to characterize reconstruction sensitivity rather than select the most favorable result.

For the 12 chain-effect events, detection membership under each of the five alternative clustering configurations was compared directly with the main 1-km/24-h component. Alternative membership was recorded as identical when exactly the same detection identifiers remained assigned to the corresponding event, and as split or merged/expanded when component structure changed. When membership was identical, the archived downstream Sentinel-1 decision remained applicable because the event definition was unchanged. When membership split or merged, no alternative radar class was imputed from main-scenario metrics because the changed event geometry and/

or timing require a new Sentinel-1 recomputation (Figure 3, Table 3). Centroid buffers of 500, 1,000, and 2,000 m were intersected with the audit grid only as precautionary exclusion zones; they were not interpreted as burned area or event extent.

### Grid audit and spatial exclusion for future research

A 1-km audit grid in EPSG:32748 was found to be inconsistent with the final 218-event inventory because it had been derived partly from an earlier 198-event reconstruction. It was therefore excluded from inference and retained only for provenance documentation. Future grid-based controls must be regenerated from the final inventory and include a temporal dimension; absence of an active-fire detection was not treated as fire absence. The final historical values for the superseded grid were 48, 28, and nine candidate cells after 500-m, 1-km, and 2-km exclusions, respectively. The earlier 28/9 wording was an incomplete two-distance excerpt of these same final historical values, not a separate result. Because the legacy grid was not used as a validated control population and was excluded from all inference, these counts are retained only as provenance documentation (Table S4).

### Sentinel-1 audit framework and label eligibility

Sentinel-1 evidence was classified deterministically as provisionally corroborated (P), partially

corroborated (PP), or unresolved (U). These states describe radar support, not confirmed fire/no-fire truth. Throughout this manuscript, corroboration refers to supporting evidence consistency and does not represent validation against confirmed fire reference data. Combining support with active-fire provenance produced A-D downstream eligibility classes, while Landsat 8/9 remained an independent evidence stream and did not revise Sentinel-1 classifications.

Sentinel-1 indicators and thresholds were developed on Development18 and then frozen before application to Evaluation60. The same processing function and numerical rules were used without manual reassessment, ad hoc scoring, or post-evaluation retuning. Although the Development18 set was limited in size, it was intentionally used only for operational rule definition and threshold freezing rather than accuracy estimation. The held-out Evaluation60 application, robustness scenarios, and leave-one-acquisition-out analyses were used to assess decision stability without post-evaluation parameter adjustment.

### Output definitions and downstream use

Primary outputs were a dated candidate-event inventory, cluster-level provenance and audit indicators, P-PP-U radar-support states, and A-D downstream eligibility classes. Event timing remained anchored to  $t_0$ , the first observed active-fire detection rather than ignition. Independent Landsat labels were retained separately

**Table 4.** Operational P-PP-U rules and robustness decisions

| Status | Main configuration                                                                                            | Robustness criterion                                                                         | Final decision                                                     |
|--------|---------------------------------------------------------------------------------------------------------------|----------------------------------------------------------------------------------------------|--------------------------------------------------------------------|
| P      | Gate passed; EVALUABLE; joint proportion contrast $\geq 0.04$ ; joint LR $\geq 1.50$ ; VV/VH LR $\geq 1.20$ . | P in $\geq 5/7$ ; P/PP support in $7/7$ ; LOO gate and strong-metric retention $\geq 80\%$ . | Provisionally corroborated; mapped to A-C according to provenance. |
| PP     | Gate passed, but one or more P conditions failed; includes LIMITED_SINGLE_SCENE.                              | P/PP support in $\geq 4/7$ , but not all robust-P conditions were met.                       | Partially corroborated; class C.                                   |
| U      | Gate failed: invalid processing/statistics, non-negative KVV/KVH, or non-positive proportion contrast.        | Main = U and U in $\geq 5/7$ , or P/PP support in $< 4/7$ .                                  | Unresolved; class D; neither positive nor negative label.          |

**Table 5.** Mapping P-PP-U status and provenance to A-D classes

| Status | Provenance                         | Class | Recommended use                                                       |
|--------|------------------------------------|-------|-----------------------------------------------------------------------|
| P      | Multi-product (MP)                 | A     | Provisional positive with the strongest radar support and provenance. |
| P      | Single-product non-singleton (SPN) | B     | Provisional positive; documented single-product provenance.           |
| P      | Singleton (S)                      | C     | Restricted use; additional verification required.                     |
| PP     | All strata                         | C     | Sensitivity analysis and priority for additional verification.        |
| U      | All strata                         | D     | Neither a positive label nor a negative label.                        |

as REF-FIRE, REF-NOFIRE, or REF-UNRESOLVED. The inventory was designed for leakage-controlled downstream analyses using only information available before  $t_0$ , appropriate temporal safety lags, and cell-time rather than static-cell units (Barbet-Massin et al., 2012). Spatial and spatiotemporal separation between model development and evaluation was also required to reduce dependence-related leakage (Roberts et al., 2017; Valavi et al., 2019). These requirements define intended downstream use and were not tested here.

### Development of the Sentinel-1 audit rule

Development18 contained 18 purposively selected events (13 from 2015 and five from 2019), all excluded from Evaluation60. Selection was designed to span provenance, singleton/chain status, image sufficiency, and radar-response variation. The set was used only to define indicators and operational thresholds; legacy visual assessments were exploratory and not reference truth.

Sentinel-1 GRD IW VV/VH imagery was restricted to matching orbit directions (Mullissa et al., 2021), with one granule retained per acquisition date. Pre- and post-event windows were  $t_0-90$  to  $t_0-15$  d and  $t_0+7$  to  $t_0+45$  d. Median composites used unique acquisitions; clusters with only one usable acquisition in either period were flagged LIMITED\_SINGLE\_SCENE.

The event zone was the union of 500-m buffers around event detections and the comparison ring extended from 1 to 3 km. Post-minus-pre VV/VH changes were summarized as KVV/KVH event-zone contrasts relative to the surrounding ring, together with changed-pixel proportions and localization ratios (Lasaponara and Tucci, 2019; Prasasti et al., 2020). Related radar workflows support the use of localized backscatter changes as corroborative surface evidence (De Luca et al., 2021; Millard et al., 2022). Comparative C- and L-band evidence further supports cautious interpretation of radar responses in Indonesian fire environments (Sudiana et al., 2025). These neighborhoods were analytical supports, not burned-area estimates.

The primary changed-pixel threshold was  $-2$  dB. The base gate required successful processing, valid statistics, negative KVV/KVH, and positive event-to-control changed-pixel contrasts. P status additionally required EVALUABLE imagery and the stronger localization/proportion criteria listed

in Table 4; base-gate events failing any P criterion were PP, including LIMITED\_SINGLE\_SCENE cases, and base-gate failures were U. All cut-offs were frozen before Evaluation60.

### Eligibility-class mapping

Final robust P required P in at least five of seven scenarios, P/PP support in all seven, and  $\geq 80\%$  retention of the base-gate and strong-evidence metrics under LOO testing. Persistent U or insufficient P/PP support retained U; remaining cases were PP. These prespecified rules were operational decision criteria, not probabilistic confidence thresholds (Table 4).

Eligibility also depended on active-fire provenance: A = P-MP, B = P-SPN, C = all PP plus P-singletons, and D = U. A/B were provisional positives, C required additional evidence, and D remained unresolved rather than negative. Thus radar strength alone could not elevate singleton events to provisional-positive status (Table 5).

### Internal robustness analysis

Robustness was evaluated across seven pre-specified configurations varying temporal windows, the changed-pixel threshold ( $-1.5$ ,  $-2.0$ , or  $-2.5$  dB), and event-buffer/control-ring geometry. Only the targeted component changed in each scenario; all metrics and classifications were recomputed to assess stability rather than optimize positivity.

For EVALUABLE clusters, LOO testing sequentially removed each usable acquisition and recomputed the relevant composites and decision metrics. LIMITED\_SINGLE\_SCENE clusters were excluded because removing their sole acquisition would leave an empty period.

### Held-out evaluation sample and algorithmic classification

After excluding Development18, the evaluation frame comprised 200 events: 21 MP, 42 SPN, and 137 singletons. A stratified random Evaluation60 sample (seed 20260724) contained 18 MP, 18 SPN, and 24 singletons. Design weights of 1.1667, 2.3333, and 5.7083 corrected unequal sampling fractions and were used only to estimate classification-state distributions in the 200-event frame (Olofsson et al., 2014).

The frozen rule was applied unchanged to all 60 events. Seven robustness scenarios produced 420 scenario records; 49 EVALUABLE clusters underwent LOO testing, generating 445 records (49 baselines and 396 acquisition-removal iterations), while 11 LIMITED\_SINGLE\_SCENE clusters were excluded from LOO by design.

Final classifications were generated programmatically from the frozen rules. Because the procedure was deterministic after freezing, inter-rater agreement was not assessed; the outputs quantify Sentinel-1 corroborative support and decision stability, not field-reference sensitivity or specificity.

### Independent Landsat optical audit

Evaluation60 was independently audited with Landsat 8/9 Collection 2 Level-2 imagery using a protocol developed without access to final Sentinel-1 classifications or robustness results. Event zones used the same 500-m geometry, and all optical thresholds were frozen before unblinding.

QA\_PIXEL and QA\_RADSAT excluded cloud, shadow, snow, fill, and saturation. Primary PRE/POST windows were t0–120 to t0–15 d and t0+7 to t0+90 d, with one prespecified fallback when coverage was inadequate. Spectral analysis required repeated clear observations over at least half of the event zone; PRE conditions used pixel-wise medians and the lowest-NBR POST observation supplied NBR, NDVI, NDMI, and MNDWI values.

REF-FIRE required adequate paired support, median dNBR  $\geq 0.15$ , a median NDVI or NDMI decline  $\geq 0.10$ ,  $\geq 10\%$  burn-like pixels, a contiguous patch  $\geq 0.5$  ha, and persistence on at least two POST dates. Water-change evidence retained REF-UNRESOLVED. REF-NOFIRE required adequate support, median dNBR  $< 0.10$ ,  $< 5\%$  burn-like pixels, no  $\geq 0.5$ -ha patch, and no persistent burn-like response; all other cases remained REF-UNRESOLVED.

Optical thresholds were prespecified audit criteria rather than universal burned/unburned definitions. Landsat was used for independent corroboration, not complete accuracy assessment; because cloud-free coverage was limited and no REF-NOFIRE case emerged, sensitivity, specificity, false-positive rate, and design-weighted optical confirmation were not estimated.

### Weighted estimation and uncertainty

Design-based inference was restricted to the 200-event evaluation frame. For classification category  $c$ , the design-weighted proportion was estimated using Equation 1:

$$\hat{P}_c = \sum_h \left( \frac{N_h}{N} \right) \hat{p}_{hc}, \quad \hat{p}_{hc} = \frac{x_{hc}}{n_h} \quad (1)$$

where:  $N_h$  and  $n_h$  are the population and sampled event counts in provenance stratum  $h$ ,  $N = 200$ , and  $x_{hc}$  is the number of sampled events in category  $c$ . The estimator accounts for unequal sampling fractions across MP, SPN, and singleton strata.

Sampling variance under stratified simple random sampling without replacement was estimated with a within-stratum finite-population correction using Equation 2:

$$\widehat{\text{Var}}(\hat{P}_c) = \sum_h \left( \frac{N_h}{N} \right)^2 \left( 1 - \frac{n_h}{N_h} \right) \frac{s_{hc}^2}{n_h} \quad (2)$$

where:  $s_{hc}^2$  is the sample variance of the binary category indicator.

Following the design-based framework described by Olofsson et al. (2014), approximate two-sided 95% Wald intervals were calculated as  $P_c \pm 1.96\text{SE}(P_c)$ , bounded to 0–1 when necessary, with the within-stratum finite-population correction retained as specified in Equation 2. These intervals quantify sampling uncertainty in the estimated distribution of algorithmic classification states within the 200-event evaluation frame; they do not quantify uncertainty in physical fire occurrence or Sentinel-1 accuracy.

### Data quality assurance and consistency verification

Before interpretation, cross-file quality assurance reconciled processing-stage counts, cluster identifiers, sampling partitions, provenance strata, P-PP-U/A-D mappings, robustness and LOO outputs, design-weighted estimates, Landsat classifications, and the blinded-versus-unblinded comparison. The preserved Inclusive\_All worksheet contains 437 harmonized detections, of which 415 are explicitly marked Retained and 22 Excluded under the main confidence rule. The 415 retained identifiers, coordinates, source products, confidence classes, and FRP values matched the archived hotspot-member table exactly.

Repository-oriented verification therefore covers record-level verification of the 437-to-415 filtering result and all downstream stages from 415 retained detections to 218 candidate events, while it does not reconstruct unavailable upstream ingestion/source-processing code. These checks assess internal integrity and reproducibility of archived outputs, not external fire validation.

## RESULTS

### Harmonization and initial distribution of active-fire detections

The harmonized archive contained 437 detections from 22 February 2015 to 29 October 2025: 50 MODIS C6.1, 80 VIIRS NOAA-20 C2, and 307 VIIRS S-NPP C2. Because repeated detections can represent the same episode, they were not treated as independent events.

Confidence filtering retained 415 detections (95.0%) and excluded 22 low-confidence records; product-level retention was 94.5–96.2% (Table 2). The high-confidence-only scenario retained only 14 detections and was used solely as a restrictive sensitivity comparison.

### Spatial characteristics of the study area

All 415 retained detections and all 218 reconstructed centroids lay within peat polygon GID 155. This confirmed spatial consistency of the

inventory but did not establish peat combustion or burned-area extent.

Spatial patterns were therefore interpreted only as geographic context within the defined study landscape.

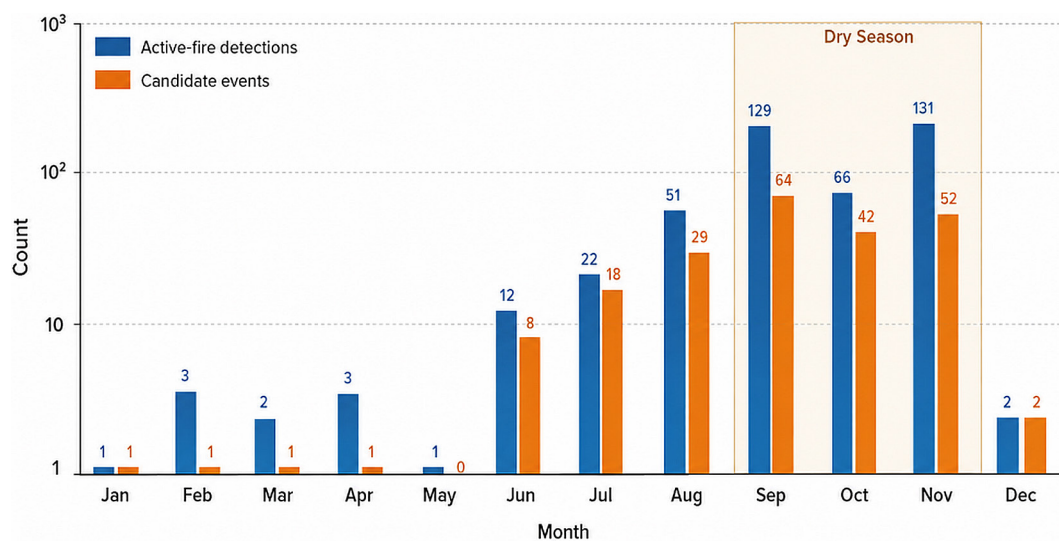
### Temporal distribution of detections and clusters

Retained active-fire detections and reconstructed candidate events were strongly concentrated in August–November: this period contained 372 of 415 retained detections (89.6%) and 186 of 218 events (85.3%). The largest annual counts occurred in 2015 (248 detections; 113 events) and 2019 (91 detections; 53 events). Because archive coverage and sensor availability varied, these counts are descriptive rather than standardized annual rates (Figure 4).

### Candidate-event reconstruction

The primary 1-km/24-h rule reconstructed 415 detections into 218 candidate events, a 47.5% reduction in analytical units. The largest event contained 11 detections. Of the 218 events, 34 (15.6%) were multi-product and 184 (84.4%) single-product, including 45 non-singletons and 139 singletons; singletons comprised 63.8% of the inventory.

Event-level chain-effect diagnostics for all six spatial-chain and all six temporal-chain cases are provided in Supplementary Table S9. Eleven



**Figure 4.** Monthly distributions of confidence-filtered active-fire detections and reconstructed candidate events based on UTC to. The shaded area indicates the August–November concentration period. Counts are displayed on a logarithmic scale

of the 12 cases have archived downstream classifications: ten Development18 events retain their frozen development-stage P/PP/U and A-D decisions, and Evaluation60 event C0217 has final status P/A; C0013 was not included in either Sentinel-1 audit subset and therefore has no downstream radar class. Table S9 also reports alternative-clustering membership changes and their implications for downstream classification.

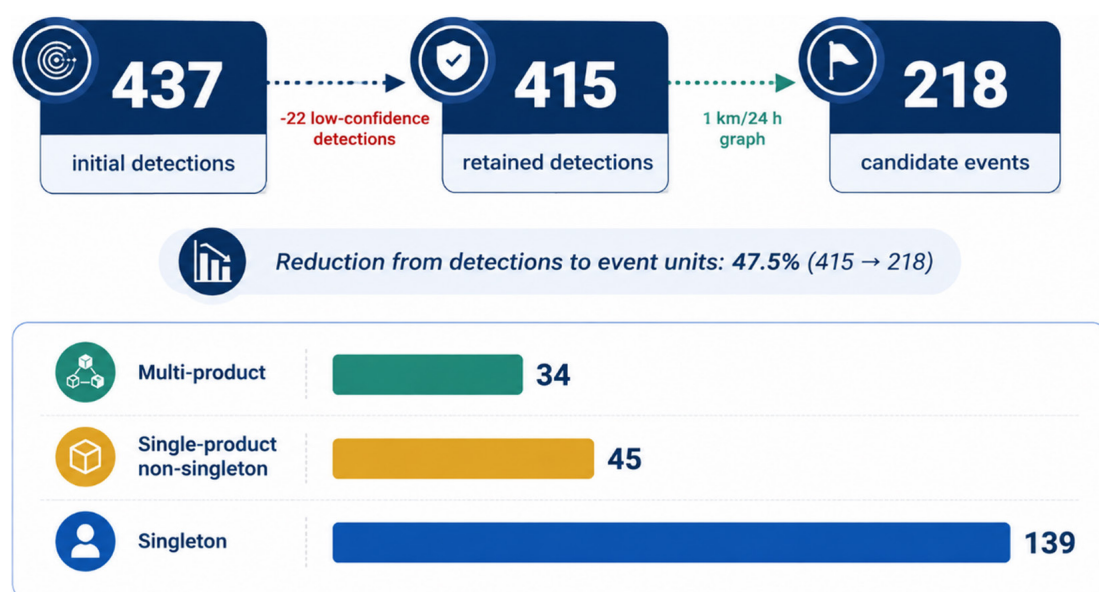
Transitive connectivity produced six events extending >1 km from the centroid and six lasting >24 h although every graph edge satisfied the pairwise 1-km/24-h rule. Across these 12 cases, the 500-m/24-h alternative split eight events, the 1-km/12-h alternative split seven, the 1-km/48-h alternative merged or expanded seven, the 1-km/72-h alternative merged or expanded eight, and the 2-km/24-h alternative merged or expanded three; the remaining cases retained identical detection membership in the corresponding scenario. For identical-membership alternatives, the archived downstream class is unchanged. For split or merged components, a valid alternative Sentinel-1 class requires reprocessing and was not inferred from main-scenario metrics. C0217 retained identical membership and P/A in four of five alternatives; under the 1-km/12-h scenario it split into three components containing 1, 1, and 2 detections, for which fragment-level radar classes were not imputed (Supplementary Table S9). Restricting the alternative-scenario comparison to the 11 chain events with archived downstream

classifications produced 55 classification-relevant event-scenario comparisons: 24 retained identical detection membership and therefore retained the same downstream classification, whereas 31 altered event identity (14 split and 17 merged/expanded). For these 31 altered comparisons, the main-scenario classification was not transferable; alternative P/PP/U and A-D classes would require recomputation of Sentinel-1 metrics for the altered event geometry and timing (Figure 5).

### Threshold and buffer sensitivity

Across the six evaluated linking configurations, event counts ranged from 174 to 266. Stricter thresholds increased fragmentation and singleton counts; broader thresholds reduced event counts but increased duration and spatial extent, confirming sensitivity to operational linkage choices. The legacy grid audit was assessed separately from the clustering-threshold sensitivity analysis and was not used to define validated control populations.

The final historical grid-audit values were 48, 28, and nine candidate-control cells after 500-m, 1-km, and 2-km exclusions, respectively. The previously stated 28/9 values were only an incomplete excerpt that omitted the 500-m result. The three values are now synchronized throughout the manuscript and Supplementary Table S4; all are retained solely for documentation and excluded from inference.



**Figure 5.** Transformation of 437 initial detections into 415 retained detections and 218 candidates, with provenance composition. The 47.5% reduction was calculated from 415 detections to 218 event units

## Development-set results and internal robustness

Development18 contained 14 EVALUABLE and four LIMITED\_SINGLE\_SCENE clusters. All 126 seven-scenario evaluations completed successfully; LOO testing of the 14 EVALUABLE clusters produced 108 records without technical failure. The finalized development rule classified nine clusters P, four PP, and five U (seven A, two B, four C, five D). Because Development18 was used to define the operational rule, this classification distribution was treated only as descriptive internal separation and not as independent evidence of accuracy. Robustness preserved the main classification for 17 of 18 development clusters (94.4%); one P case was downgraded to PP. Development18 remained excluded from Evaluation60 and all design-based estimates.

## Frozen-rule application to the held-out evaluation sample

Applied unchanged to Evaluation60, the frozen rule initially yielded 18 P, 20 PP, and 22 U. Following robustness and LOO analyses, final

classifications were 15 P (25.0%), 24 PP (40.0%), and 21 U (35.0%); three P cases were downgraded to PP and one U reassigned to PP. Thus 39/60 events had at least partial radar support. Final A-D mapping was 5/7/27/21 (Table 6).

Negative KVV and KVH occurred in 41 Evaluation60 events, including all P/PP cases and two U cases. Within the frozen rule, jointly negative KVV and KVH were necessary but not sufficient for P/PP support; localization, changed-pixel proportions, image sufficiency, and robustness also influenced final status (Figure 6).

## Independent Landsat optical audit

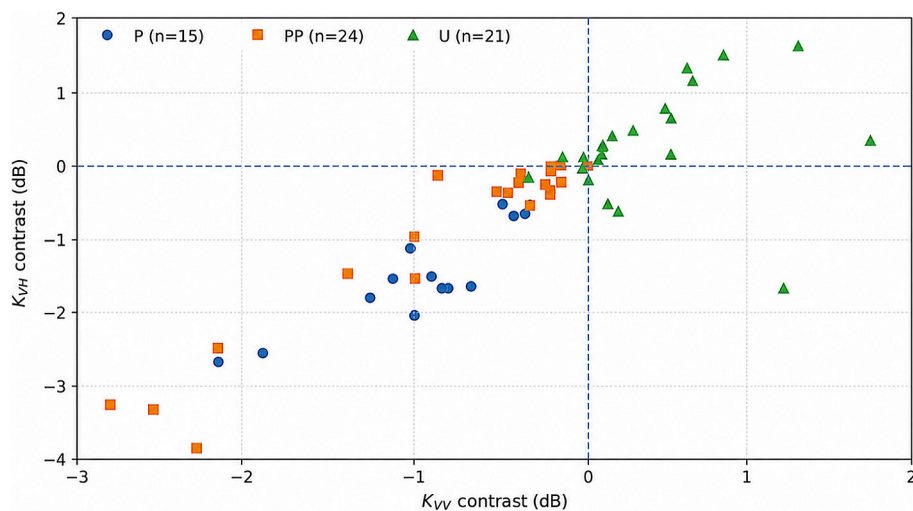
Of 60 evaluation events, 26 passed Landsat image-sufficiency screening and seven met REF-FIRE criteria; 19 were spectrally unresolved and 34 lacked adequate PRE/POST coverage. No REF-NOFIRE case was identified. Unresolved outcomes reflected water confounding, insufficient dNBR response, or inadequate paired support.

All seven REF-FIRE events were Sentinel-1-supported (two P, five PP, zero U). The remaining optical outcomes were distributed across P/

**Table 6.** Final classification distribution in the stratified random evaluation sample

| Stratum | n  | P  | PP | U  | P + PP | Classes A/B/C/D |
|---------|----|----|----|----|--------|-----------------|
| MP      | 18 | 5  | 9  | 4  | 14     | 5/0/9/4         |
| SPN     | 18 | 7  | 6  | 5  | 13     | 0/7/6/5         |
| S       | 24 | 3  | 9  | 12 | 12     | 0/0/12/12       |
| Total   | 60 | 15 | 24 | 21 | 39     | 5/7/27/21       |

**Note:** MP – multi-product; SPN – single-product non-singleton; S – singleton. Values are unweighted sample counts.



**Figure 6.** KVV and KVH contrasts in the main configuration for 60 clusters by final label. Points in the negative quadrant may remain PP/U when localization, robustness, or image sufficiency does not satisfy P criteria

**Table 7.** Landsat optical-audit outcomes in Evaluation60 by final Sentinel-1 status

| Optical outcome     | n  | P  | PP | U  |
|---------------------|----|----|----|----|
| REF-FIRE            | 7  | 2  | 5  | 0  |
| REF-NOFIRE          | 0  | 0  | 0  | 0  |
| Spectral unresolved | 19 | 3  | 7  | 9  |
| Image insufficient  | 34 | 10 | 12 | 12 |
| Total               | 60 | 15 | 24 | 21 |

**Note:** Optical labels were frozen before unblinding to Sentinel-1. “Spectral unresolved” denotes an inconclusive or confounded optical result, while “Image insufficient” denotes inadequate PRE/POST coverage; neither is a no-fire class.

PP/U as shown in Table 7. Because REF-UNRESOLVED and image-insufficient cases were not negative references, the comparison was interpreted as independent corroboration rather than an accuracy assessment.

Design weighting for the 200-event evaluation frame estimated frame proportions of 19.65% P (95% CI 10.43–28.86%), 37.94% PP (25.09–50.78%), and 42.42% U (29.24–55.59%). P+PP was 57.58% (44.41–70.76%), compared with the unweighted Evaluation60 proportion of 65.0%.

Weighted A-D proportions were 2.92%, 8.17%, 46.50%, and 42.42%, respectively, indicating that most events either required additional evidence or remained unresolved (Table 8).

### Data-integrity and reproducibility checks for archived outputs

Cross-file verification reproduced the 437-to-415 record-level filtering result (415 Retained and 22 Excluded records), the 415-to-218 detection-to-event lineage, all 60 final Evaluation60 labels (15 P, 24 PP, 21 U), the A-D distribution (5/7/27/21), the weighted P+PP estimate of 57.58% (95% CI 44.41–70.76%), and Landsat

totals (7 REF-FIRE, 19 spectral unresolved, 34 image-insufficient). The 415 retained identifiers and key attributes matched between the preserved pre-filter workbook and the archived hotspot-member table. These checks support internal consistency and record-level reproducibility of the preserved analytical data, but they do not constitute external accuracy validation and do not recreate unavailable upstream ingestion or original image-processing code.

## DISCUSSION

### Implications for event reconstruction and source traceability

Reconstructing 415 retained detections into 218 candidate events reduced analytical units by 47.5%, demonstrating the pseudo-replication that can arise when repeated sensor observations are treated independently (Oom et al., 2016; Balch et al., 2020). This result is consistent with the need for explicit event-level reconstruction in multi-source fire archives (Bernini et al., 2026).

**Table 8.** Estimated totals, weighted proportions, and 95% CIs in the 200-cluster evaluation frame

| Stage    | Class | Estimated total (N=200) | Weighted proportion (95% CI) |
|----------|-------|-------------------------|------------------------------|
| P-PP-U   | P     | 39.29                   | 19.65% (10.43–28.86%)        |
| P-PP-U   | PP    | 75.88                   | 37.94% (25.09–50.78%)        |
| P-PP-U   | U     | 84.83                   | 42.42% (29.24–55.59%)        |
| A-D      | A     | 5.83                    | 2.92% (2.07–3.76%)           |
| A-D      | B     | 16.33                   | 8.17% (4.49–11.85%)          |
| A-D      | C     | 93.00                   | 46.50% (33.27–59.73%)        |
| A-D      | D     | 84.83                   | 42.42% (29.24–55.59%)        |
| Combined | P+PP  | 115.17                  | 57.58% (44.41–70.76%)        |

**Note:** intervals quantify sampling uncertainty in the distribution of algorithmic classifications, not uncertainty about fire occurrence. Categories with small samples should be interpreted with their sample sizes and inferential limits.

Transitive connectivity also matters: six events extended >1 km from their centroids and six lasted >24 h despite every graph edge satisfying the 1-km/24-h rule. Event-level auditing showed that stricter alternatives frequently fragmented these chain events (8/12 under 500-m/24-h and 7/12 under 1-km/12-h), whereas temporal or spatial relaxation merged/expanded subsets of them (7/12 under 1-km/48-h, 8/12 under 1-km/72-h, and 3/12 under 2-km/24-h). This demonstrates that chain effects can materially change event identity even when pairwise links are valid. Downstream classes can be carried across only when detection membership is identical; split/merged alternatives require event-specific reprocessing rather than label transfer.

Detection provenance was informative but not definitive. Partial-or-strong Sentinel-1 support occurred in 14/18 MP, 13/18 SPN, and 12/24 singleton events, but multi-product status did not guarantee radar support and single-product events could still show coherent responses (Schroeder et al., 2014; Giglio et al., 2016). Similar limitations of cross-product agreement have been reported in multi-sensor active-fire analyses (Briones-Herrera et al., 2020). Keeping provenance and radar corroboration separate prevented either evidence stream from dominating eligibility decisions: three singletons reached P, whereas four MP events remained U.

### **Interpretation of radar evidence and unresolved cases**

P or PP classifications comprised 65.0% of Evaluation60 but 57.58% after design weighting; U was the largest weighted category (42.42%, 95% CI 29.24–55.59%). Unlike a burned-area or fire/no-fire label, U here denotes insufficient or unstable Sentinel-1 corroborative evidence, not an unburned condition.

Negative KVV/KVH alone did not determine support: 24 events with negative contrasts were PP and two remained U. Moisture, inundation, clearing, harvesting, and vegetation or surface-structure change can generate overlapping C-band responses (De Luca et al., 2021; Millard et al., 2022). Final decisions therefore also required localization, image sufficiency, robustness across scenarios, and LOO stability, consistent with the need for multi-criterion interpretation of radar fire evidence (Sudiana et al., 2025).

Legacy candidate-control cells lacked temporal matching and came from a superseded

reconstruction. Future controls should therefore be independently constructed as matched cell-time units accounting for season, year, land cover, hydrological context, and sensor availability (Barbet-Massin et al., 2012; Roberts et al., 2017). Spatial and spatiotemporal dependence should also be addressed explicitly during validation (Valavi et al., 2019).

### **Independent optical corroboration**

The frozen Landsat audit provided evidence independent of Sentinel-1 while also illustrating the practical limits of optical verification in cloudy tropical peatlands. Only 26/60 events had sufficient repeated clear observations, and seven met the conservative REF-FIRE criteria; all seven were already P/PP. This concordance strengthens the evidence for those seven events but does not establish that all P/PP events were true fires or that U events were non-fire.

Optical uncertainty remained substantial: 34 events lacked sufficient repeated PRE/POST coverage, nine had potential water confounding, three lacked adequate paired observations, and no event met REF-NOFIRE. Hydrological change can alter optical indices in drained or seasonally drying peatlands (Ismail et al., 2021; Taufik et al., 2022). Radar backscatter is likewise sensitive to wetness-related surface conditions (Millard et al., 2022).

Retaining unresolved optical outcomes rather than forcing uncertain cases into negative labels preserved uncertainty and followed reference-data governance principles (Franquesa et al., 2022).

### **Label governance and modeling implications**

Mapping P-PP-U support to A-D classes converted uncertainty into explicit downstream rules. Only 12/60 evaluation events entered provisional-positive classes A/B; 27 class-C events required additional evidence and 21 class-D events remained outside the positive set. Class C was retained as an intermediate category rather than a weak negative (Franquesa et al., 2022).

For downstream use, A/B are the primary provisional-positive set, C should be reserved for sensitivity analysis or further independent verification, and D should remain outside both positive and negative sets. Background observations should be constructed independently as

temporally and environmentally matched cell-time controls rather than inferred from D.

The inventory is best used as an evidence-screening and label-governance resource alongside canals, land cover, hydrology, access, and operational records, not as a substitute for burned-area or hazard products. Peat hydrology and drainage remain important controls on fire susceptibility and persistence (Horton et al., 2021; Taufik et al., 2022). Land-use change and broader peatland biogeochemistry provide additional landscape context (Page et al., 2022). Recent work also emphasizes governance and landscape-scale organization of peat-fire risk (Abdurrahim et al., 2026; Sutikno et al., 2026).

### **Inferential scope and transferability**

The weighted P/PP/U estimates apply only to the 200-event evaluation frame under the stated stratified sampling design. They describe Sentinel-1 corroboration states rather than fire prevalence, sensor sensitivity, or burned extent. Transferability beyond this landscape, archive, sensor configuration, and frozen audit procedure requires prospective testing of the unchanged workflow without site-specific retuning.

### **Limitations and validation priorities**

Several limitations constrain interpretation. The Sentinel-1 rule was developed on only 18 purposively selected events, so although Development18/Evaluation60 separation and rule freezing reduce post-hoc tuning, external validation of the unchanged rule remains necessary.

The Landsat audit provided only partial independent corroboration: 26/60 events passed image sufficiency, seven met REF-FIRE, and none met REF-NOFIRE. Sensitivity, specificity, false-positive rate, overall error, and burned-area accuracy therefore cannot be estimated; likewise, 56/60 stable Sentinel-1 decisions reflect internal robustness rather than classification truth.

Sentinel-1 responses were not fire-specific, comparison rings were not explicitly hydrology- or land-cover-matched, 11 events lacked enough acquisitions for LOO testing, and Landsat was constrained by persistent cloud and water-related confounding. Temporal coverage and sensor composition also varied across the archive.

End-to-end computational reproducibility remains limited by unavailable upstream

ingestion/download code, the original Sentinel-1 source-processing code, the original end-to-end analytical pipeline, and several Landsat image-sufficiency raw exports. However, the preserved 437-row Inclusive\_All worksheet and its explicit main-analysis status field allow record-level verification of the 437-to-415 filtering result, and the archived package supports independent verification from those retained records through event reconstruction, Sentinel-1 classifications, Landsat audit, and design-weighted summary stages. Unavailable image-processing or numerical source materials were not reconstructed or imputed.

Future validation should combine the unchanged radar/optical workflow with temporally matched controls, operational or field evidence, and independent peatland landscapes before any site-specific recalibration. Such prospective testing would address transferability and physical validity without retrospectively altering the frozen evidence rules evaluated here.

## **CONCLUSIONS**

Of 437 harmonized MODIS/VIIRS detections, 415 passed confidence filtering and were reconstructed into 218 candidate events under the pre-specified 1-km/24-h graph rule, reducing analytical units by 47.5% while preserving event timing, detection provenance, chain effects, and uncertainty.

Following robustness and leave-one-acquisition-out analyses, Evaluation60 comprised 15 P, 24 PP, and 21 U events; 56/60 primary decisions were stable, and the design-weighted estimated P+PP proportion was 57.58% (95% CI 44.41–70.76%). Provenance-aware A-D classes prevented radar evidence alone from determining downstream label eligibility. The independent Landsat 8/9 audit identified seven REF-FIRE events, all within the Sentinel-1-supported group; no event met the conservative REF-NOFIRE criteria, and the remaining 53 optical outcomes were unresolved because of insufficient or inconclusive evidence. The optical audit therefore strengthened a limited subset of candidate events rather than providing a complete accuracy reference.

Overall, the workflow converts repeated multi-sensor active-fire detections into auditable candidate events while keeping detection provenance, corroborative evidence, and downstream eligibility conceptually distinct. It reduces pseudo-replication without forcing uncertainty into binary labels and

provides a defensible foundation for subsequent leakage-controlled candidate-event monitoring and evidence-aware predictive analyses.

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