A Global Event-Based Benchmark for Tide and Surge Models Beyond the Tide Gauge

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Abstract

Coastal flood hindcasting and forecasting form the foundation of effective risk management in coastal regions. They drive emergency response efforts and inform the design of coastal defenses, adaptation strategies, and evidence-based policy. Global coastal sea level models are traditionally validated using time-series regression metrics (i.e., Root Mean Square Error [RMSE], Mean Absolute Error [MAE], Pearson correlation) at tide gauge sites. However, this approach has two main drawbacks: (1) gauge coverage is geographically sparse outside North America, Northern Europe, and limited parts of Asia, and (2) spatially aggregated metrics obscure prediction errors during extreme sea level events. Here we introduce a novel event-based framework that benchmarks models against a global database of news-reported flood events captured in the Groundsource database. Our curated benchmark of ~33,000 global coastal flood records across 10 years was constructed using a Large Language Model (LLM) calibrated with tide-gauge data to identify coastal floods. Evaluating the performance of two global storm tide reanalyses, namely Global Tide and Surge Model (GTSM) simulations and Environment and Climate Change Canada's (ECCC) hindcast, against our curated flood database, reveals detection rates of only 39% (GTSM) and 43% (ECCC), with nearly half of all flood reportings missed by the two models. Further, we show that spatial aggregation, such as averaging RMSE across the gauges of a country, can mask flood impacts, whereas per-gauge extreme-quantile errors align more closely with performance measured on records of actual floods. This framework offers an essential complementary lens for assessing model quality by providing broad global coverage beyond gauge locations.

Introduction

Coastal flooding ranks among the most destructive and costly natural hazards globally, with damages projected to increase dramatically under climate change, continued coastal population growth and urbanization, and decline in natural habitats (such as saltmarshes, coral reefs or mangroves) that act as a natural buffer to flooding [1, 2]. Reliable prediction of extreme coastal water levels, driven by storm surge, astronomical tides, waves, and their compound interactions, is critical for early warning systems, infrastructure planning, and climate adaptation. Global storm tide models, such as the Global Tide and Surge Model (GTSM, [3]) and the Environment and Climate Change Canada's (ECCC) hindcast [4], are essential tools for these purposes, providing continuous water level predictions across the world's coastlines.

The standard approach to evaluating storm tide models relies on comparison against tide gauge observations from datasets such as the Global Extreme Sea Level Analysis (GESLA, [5]). While GESLA provides high-quality, long-term water level data, its spatial coverage is uneven. The ~4,500 coastal stations are heavily concentrated in a few data-rich regions including North America, Northern Europe, and Japan, while other regions, particularly in the Global South (e.g., Indonesia, South America, India, and Africa), have substantially sparser observational networks despite experiencing frequent and severe coastal flooding [6, 7]. This creates a profound monitoring gap: model performance is primarily certified in the regions where observational density is highest, while remaining poorly validated in the regions where accurate forecasting is often most critical for vulnerable populations, and flood defences are not yet established. Previous global reanalysis studies have noted systematic underestimation of extreme sea levels in precisely these data-sparse regions [8], further underscoring the need for evaluation approaches that do not depend on gauge density.

Even where tide gauge data are available, the conventional evaluation paradigm suffers from a more subtle problem related to how metrics are summarized. Standard time-series regression metrics, such as Root Mean Square Error (RMSE), Mean Absolute Error (MAE), Pearson correlation, are typically computed for individual stations. At extreme quantiles (e.g., q=0.99), these metrics do correlate meaningfully on a per-station level with the ability to capture flood events. However, large-scale model validation studies usually aggregate these per-station metrics into regional or global averaged statistics [9, 10]. These aggregates give equal weight to every station, regardless of whether that station experiences extreme events or not. A station in a sheltered bay with excellent tidal reproduction but no significant surge events contributes equally to the summary score as a station at an exposed hurricane landfall location. Consequently, regional RMSE, MAE, or Pearson correlation scores are dominated by the majority of stations where conditions remain benign, producing summary statistics that can mask poor performance precisely where it matters most.

To address both the imbalanced gauge distribution and the drawbacks of validation statistics aggregation, we propose a complementary evaluation paradigm: benchmarking model predictions against a global database of real-world coastal flood events. Rather than asking "how well does the model reproduce the water level time series at gauge stations?", we ask "does the model correctly predict the occurrence of coastal conditions associated with observed flood events?"

Event-based validation approaches have been explored in related domains, including inland flood inundation mapping [11], satellite precipitation assessment [12], and flash flood forecasting [13], but have not been applied at global scale to coastal storm tide models. This study addresses that very gap. Recent studies have demonstrated the viability of using natural language processing and LLMs to extract ground-truth flood data from news media and web sources. For instance, Pabari et al. [14] used natural language processing classifiers to extract localized flood events from news to validate satellite-based flood insurance, while Colverd et al. [15] developed FloodBrain, an LLM-based system using retrieval-augmented generation to synthesize flood disaster impact reports. However, while these studies establish news media as a reliable proxy for general flood occurrences, applying this algorithmic paradigm to global coastal flood benchmarking introduces a unique challenge: semantic ambiguity.

News-derived events provide broad spatial coverage across every inhabited coastline where journalists report, but they introduce substantial semantic noise: near-coast pluvial, fluvial, and flash floods are frequently described using language indistinguishable from true coastal extreme water events. To overcome the semantic noise inherent in journalist reports, we use the GESLA tide gauge dataset during an initial calibration step which systematically refines our extraction of tide/surge-driven flood events. The resulting calibrated framework is then applicable globally, including regions that lack physical tide gauges. Our approach leverages the Groundsource database [13], a global repository of over 2.6 million flood records extracted from news articles using the Gemini LLM.

The key contributions of this paper are threefold. First, we develop a scalable LLM-based framework for constructing curated coastal flood benchmarks that filter the Groundsource database into a dataset of ~33,000 coastal flood records spanning 2015–2025. Second, we present the first global event-based evaluation of coastal flood models, assessing two reanalysis products against this benchmark and quantifying hit rates, miss rates, and peak water-level errors. Third, through country- and station-level spatial analyses, we demonstrate that conventional aggregated performance metrics can obscure model skill during extreme water level events, while errors in station-specific extreme quantiles provide a much closer representation of event-based performance.

Results

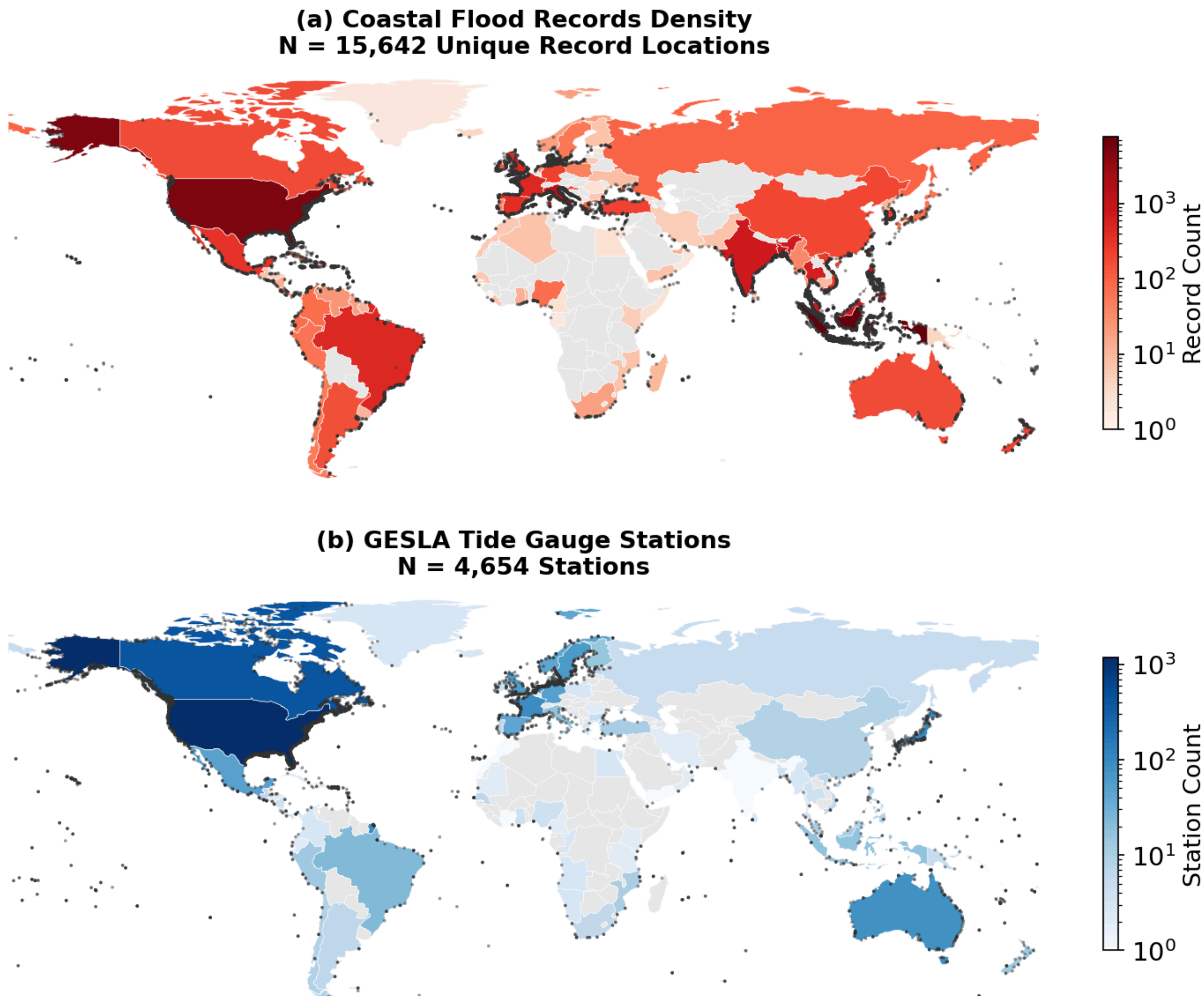
Our analysis consists of three stages: (1) constructing a curated coastal flood benchmark from news-derived events using LLM-based filtering calibrated against tide gauge data, (2) evaluating model predictions using both supervised station-level metrics and unsupervised event classification, and (3) comparing event-based and classic evaluation paradigms at multiple spatial scales. The Methods section provides full methodological details.

Benchmark Construction

The Groundsource database captures a broad spectrum of flood events, including those caused by fluvial, pluvial, groundwater, or dam-break mechanisms. When adapting this generic dataset for our study, we had two primary objectives: first, to isolate only those events driven exclusively by coastal processes (astronomical tides, storm surge, and waves); and second, to significantly elevate the dataset's overall precision in capturing true cases of flooding. To accomplish these two goals, we developed region-specific LLM prompts through an iterative, human-in-the-loop process calibrated against the GESLA tide gauge dataset.

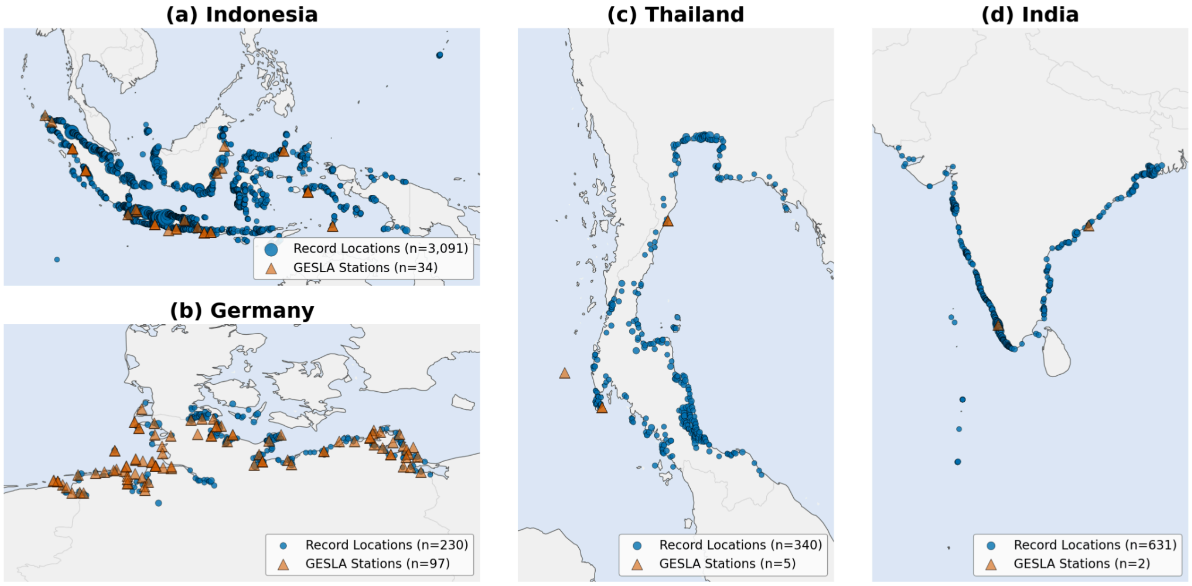
The outcome of this prompt engineering process are tailored per-region classifiers, adapted to the reporting styles and meteorological contexts of six global regions. Each classifier takes as input flood reports from Groundsource and decides whether a given report pertains to a coastal flood event. We validated the quality of these classifiers on a spatially held-out test set (n=2,005 across all regions). Prior to any post-processing, the raw Groundsource archive achieved a precision of 60% [13]. The classifiers improved upon this baseline and yielded a final overall precision of 92.8% at a recall of 35.9%. This performance was robust across the globe; full regional evaluation metrics (including precision, recall, and F1 scores for training and test splits across all iterations and country breakdowns) are available in Supplementary Material S1.

Our final benchmark corpus comprises 33,293 verified coastal flood records spanning 115 countries, compared to the 4,654 GESLA gauge stations available for traditional validation. Despite comparable country counts, the spatial distributions of these two data sources are substantially different. Figure 1 illustrates the spatial bias of gauges toward North America, Japan, and Europe, compared to the broader and more balanced distribution of the event-based benchmark.



[Figure 1] *Global choropleth maps showing log-scaled counts of records per country (a) and GESLA stations per country (b), overlaid with individual coordinate scatter points.*

The spatial mismatch is particularly evident when examined at the national scale, as shown in Figure 2 for Indonesia, Thailand, India, and Germany. Indonesia (Figure 2a) exhibits the highest global frequency of news-reported coastal flood occurrences, and yet possesses only 34 GESLA stations across 54,000 km of coastline. Consequently, the vast majority of the 3,091 locations where flooding was reported (a ratio of 1 station per 91 locations) remain unvalidated through traditional observational metrics. India (Figure 2d) displays a similar pattern with 631 unique locations where flooding was reported versus only 2 tide gauge stations (ratio of 1:315). In stark contrast, Germany (Figure 2b) maintains a much higher density with 97 GESLA stations relative to 230 locations where flooding was reported (ratio of 1:2).



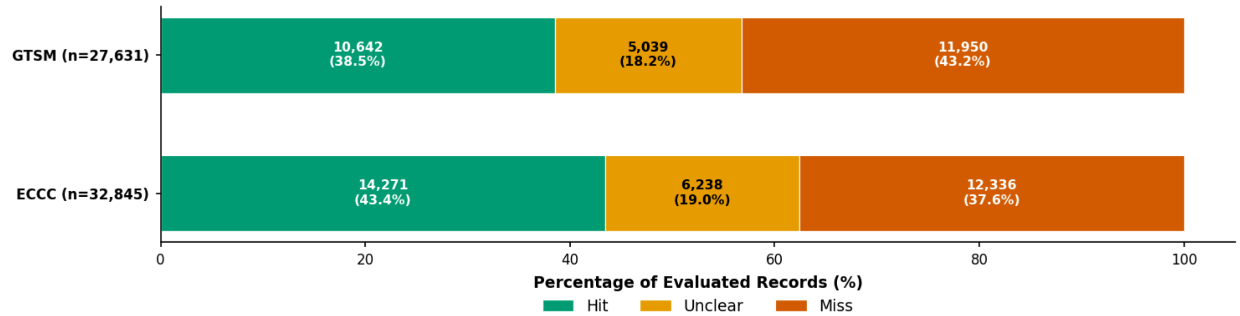
[Figure 2] *Country-level zoom maps for (a) Indonesia, (b) Germany, (c)Thailand, and (d) India, showing locations where coastal flooding was reported (blue dots) vs. GESLA tide gauge stations (orange triangles).*

Model Evaluation

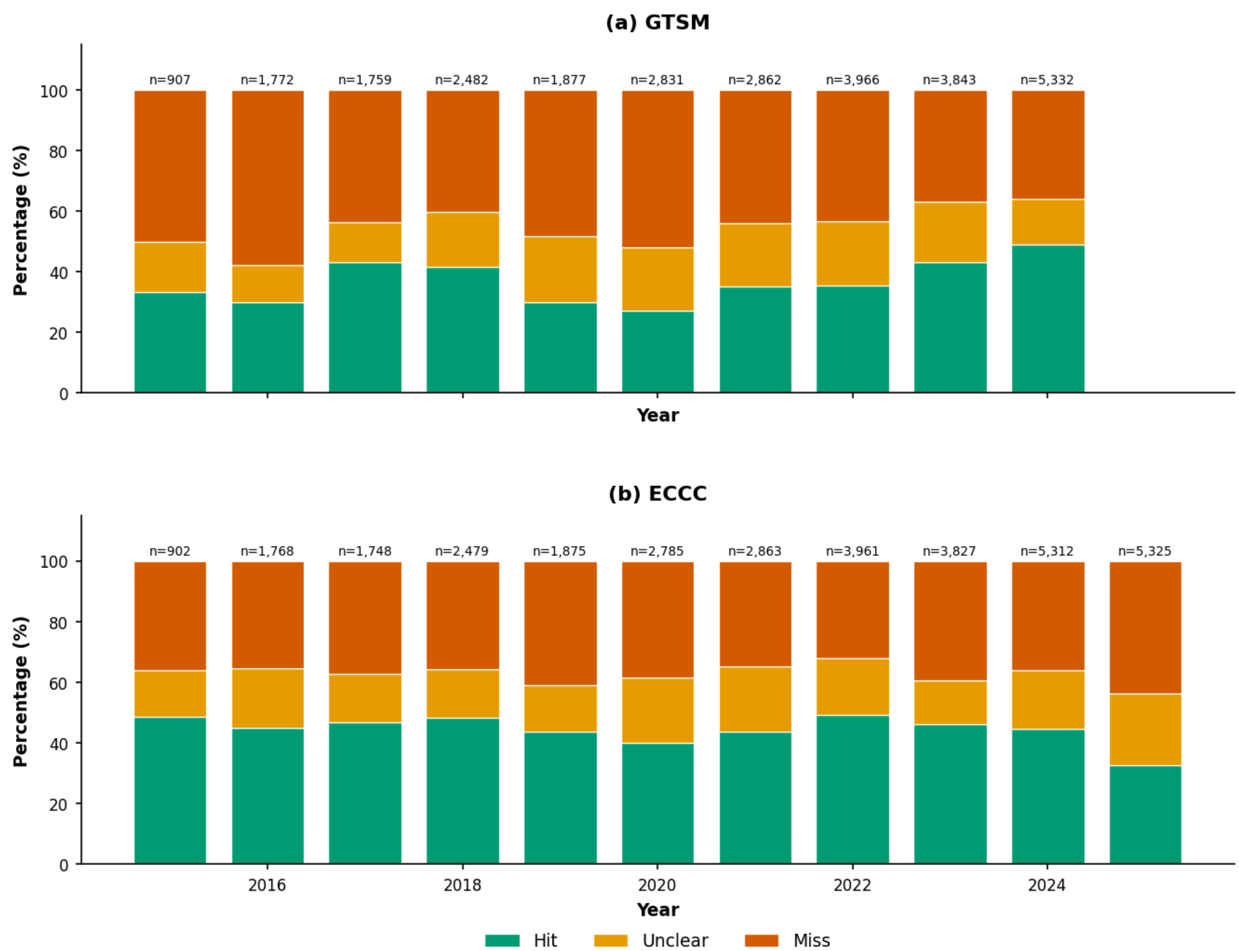
To evaluate the performance of storm tide models, we categorize each model's prediction for every reported flood record into one of three classifications: a 'hit,' a 'miss,' or 'unclear.' A prediction is considered a ‘hit’ if the modeled water level exceeds a 2-year return period within the time span extracted from the flood record. We assign a ‘miss’ if the modeled water level during the record corresponds to a return period of less than 1.1 years. Predictions falling in the intermediate range (1.1 to 2.0 years) are classified as ‘unclear,’ so that we do not penalize predictions that were only slightly too low. While localized inundation can occur at lower return periods, sub-2-year water levels heavily overlap with routine high water, which makes it difficult to reliably distinguish such flood events from non-flood conditions at a global scale.

As illustrated in Figure 3, of the 27,631 records of reported coastal flooding evaluated within GTSM's temporal coverage (2015–2024), this model successfully detected 10,642 (38.5%) instances as hits, while 11,950 (43.2%) reported floods were missed, and 5,039 (18.2%) fell in the unclear range. ECCC, which was evaluated over a slightly longer span (2015–2025) comprising 32,845 records, had 14,271 (43.4%) report floods as hits, 12,336 (37.6%) instances as missed, and 6,238 (19.0%) instances classified as unclear.

Examining annual hit rates reveals distinct temporal patterns, as shown in Figure 4. GTSM (Figure 4a) shows fluctuating performance over the evaluated decade, ranging from 27.1% in 2020 to a peak of 49.0% in 2024. ECCC (Figure 4b) shows relatively stable performance over 2015–2024, ranging between 40.1% and 49.3%, with a decrease to 32.7% in 2025. The number of evaluated records per year also increases steadily for both models, from around 900 in 2015 to approximately 5,300 in 2025, due to a high number of reported coastal flood events in the Groundsource database in more recent years.

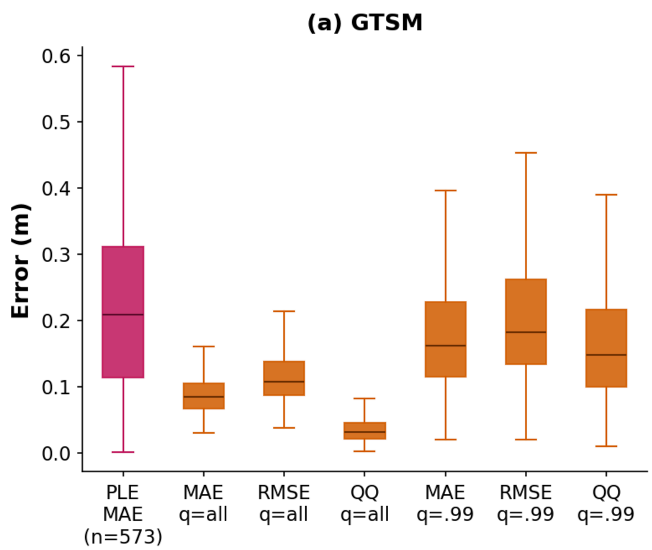


[Figure 3] *Horizontal stacked bar chart showing the percentage of Hit (green), Unclear (orange), and Miss (red) classifications for GTSM and ECCC across all evaluated records.*



[Figure 4] *Vertical stacked bar charts showing Hit/Unclear/Miss proportions by year, for both GTSM (a) and ECCC (b).*

Supervised Station-Level Evaluation. For events co-located with GESLA stations, we compute the Peak Level Error (PLE), the difference between the model's predicted and observed maximum water levels during the event, alongside standard time-series regression metrics. Focusing on the supervised pairs where flood records intersect with GESLA data, we directly compare event-based versus classic errors at the individual station level. For each station, we compute the PLE for every co-located event and then take the MAE across events to produce a per-station PLE MAE (i.e., the mean absolute peak level error per station). Figure 5 shows the distributions of per-station PLE MAE alongside classic metrics for both the full time series and extreme tail ($q = 0.99$).



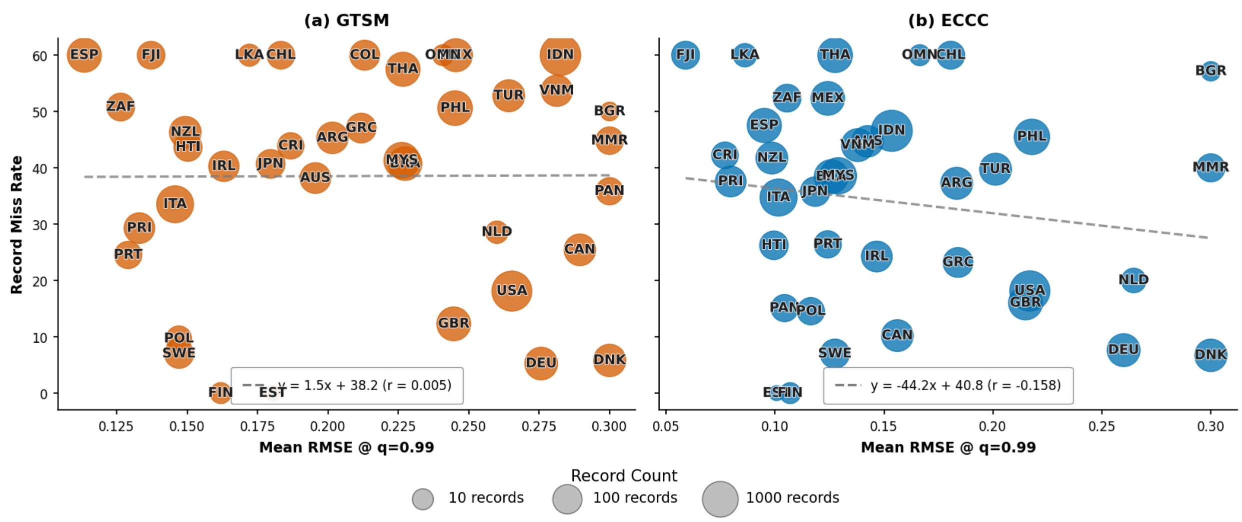
[Figure 5] *Box plots comparing station-level distributions of Peak Level Error (PLE MAE) against classic metrics (RMSE, MAE, Quantile–Quantile (QQ) for the full time series and at q=0.99), one panel per model.*

The per-station Peak Level Error is substantially larger than the full time series MAE, but comparable in magnitude to the extreme-quantile MAE and RMSE at $q = 0.99$. This correspondence is both expected and reassuring: at stations that do experience coastal flooding, those events constitute the extreme tail of the local water level distribution, so the event-based and high-quantile classic errors should converge. Indeed, they exhibit correlations of 0.62 for GTSM and 0.63 for ECCC (the corresponding scatter plot can be seen in Supplementary Figure S2). This agreement serves as a sanity check for our event-based metric.

However, this analysis is restricted to the subset of stations that have co-located events. The majority of GESLA stations do not intersect with any detected flood event during the study period. When all stations are included in aggregated summaries, the stations without events dilute the extreme-tail signal, producing optimistic summary scores that do not reflect performance at the locations where flooding actually occurs. This distinction becomes central in the aggregation analysis that follows.

Spatial Comparison of Flood Record- and Tide-Based Evaluation

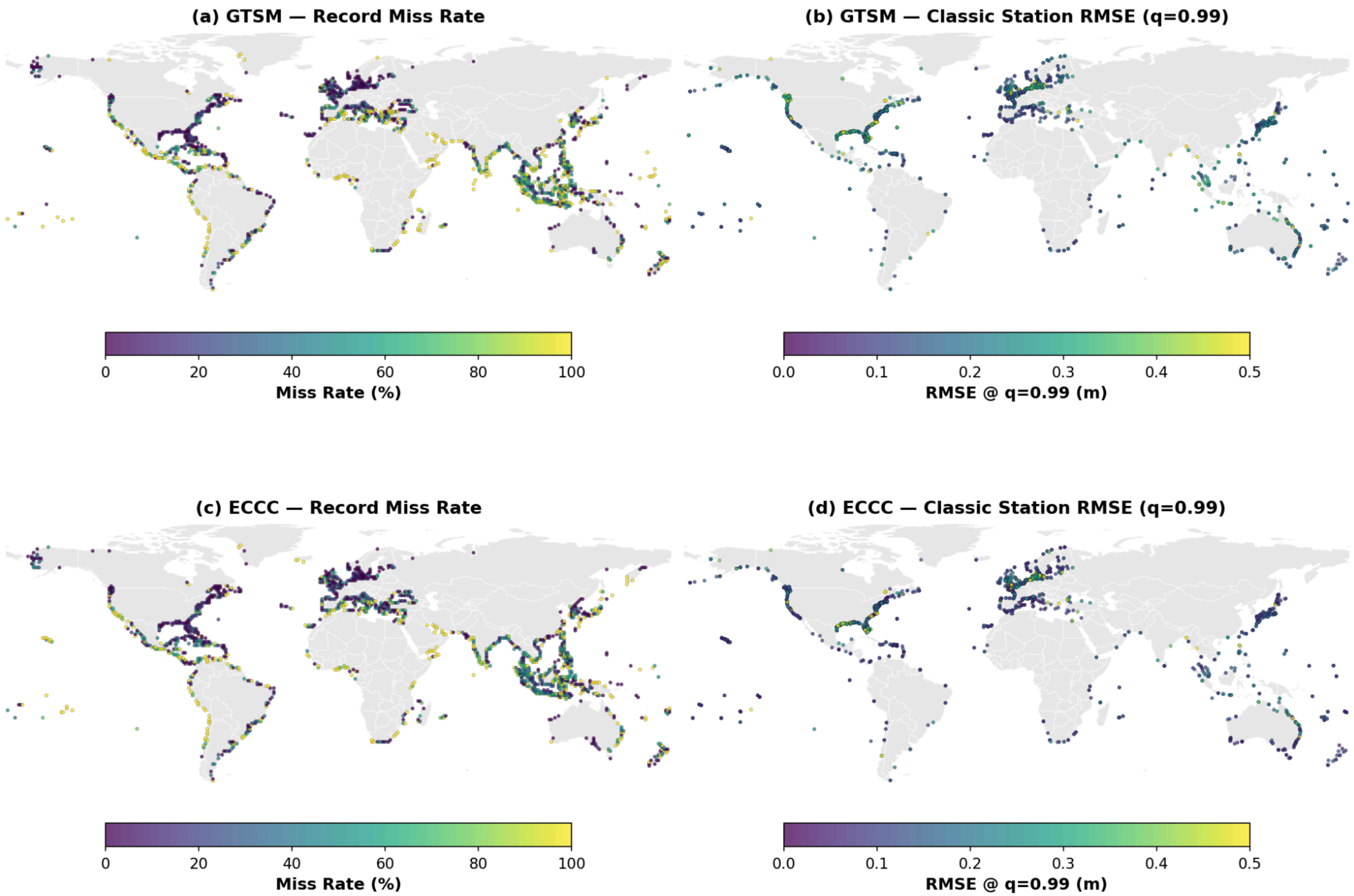
To establish a common spatial denominator between the geographically disparate event-based and classic evaluation paradigms, we aggregated both metric families to the country level. After filtering to countries with at least 3 flood reports and 3 tide gauge stations, 47 countries remain for comparison for GTSM and 33 for ECCC. Comparing unweighted country-level averages, the miss rate exhibits essentially zero correlation with classic RMSE for GTSM (Figure 6a, $r = 0.005$), weak negative correlation for ECCC (Figure 6b, $r =- 0.16$). Supplementary Tables S3.1 and S3.2 provide the full results with all countries and metrics.



[Figure 6] *Scatter plots of country-level event miss rate vs. RMSE at q=0.99 with bubble size proportional to log(record count) and country labels. Regression lines with R^2.*

This is a striking result, considering how ubiquitous RMSE is as an evaluation metric. The explanation for this observation is rooted in an aggregation problem: within each country, classic metrics are averaged across all stations, including those in locations that experience no significant extreme water levels or flooding. Event metrics, on the other hand, are computed only at locations where floods actually occurred. A country can thus exhibit low average RMSE (because most of its stations are in quiescent locations) while simultaneously failing to detect the majority of real coastal flood events that occur along its more exposed coastlines.

If we further break down the spatial granularity and compare results at individual tide gauge locations with record locations within a 1° grid, the spatial decoupling between classic and event-based metrics becomes visually apparent, as shown in Figure 7. The event-based miss rates show more distinct and regionalized spatial patterns: detection capabilities are markedly superior along the US East Coast and throughout Northern Europe, while tropical coastlines and the Global South exhibit poorer hit rates. This contrast underscores how the event-based evaluation paradigm exposes regional performance disparities in flood detection that remain largely hidden when evaluating point-based classic metrics.



[Figure 7] *Side-by-side scatter maps comparing event-based miss rate at record centroids (binned to 1° buckets, a, c) vs. classic RMSE at q=0.99 at GESLA station locations (b, d), for both GTSM (a, b) and ECCC (c, d).*

The regional disparity is explicitly quantified by analyzing the performance breakdown between data-rich regions (US, Northern Europe, and Japan) and the rest of the world. For GTSM, strong detection capabilities are seen in the data-rich regions (n=8,175) with a 69.0% hit rate and a 17.5% miss rate (13.5% unclear), but its performance drops sharply in the rest of the world (n=19,456) to a hit rate of only 25.7% and a miss rate of 54.1% (20.2% unclear). Similarly, for ECCC, the data-rich regions (n=8,757) achieve a high hit rate of 70.4% and a low miss rate of 17.4% (12.2% unclear), whereas the rest of the world (n=24,088) exhibits a considerably lower hit rate of 33.6% and a higher miss rate of 44.9% (21.5% unclear). Supplementary Figure S4 provides the corresponding figure to illustrate this regional breakdown.

Discussion

A central finding of this study is the disconnect between aggregated classic regression metrics and flood reporting-based detection performance at the country level, despite reasonable per-station alignment at the extreme quantile. At the level of individual stations, extreme-quantile RMSE ($q = 0.99$) and event-based Peak Level Error are strongly correlated, confirming that both frameworks capture similar information about a model's accuracy during extreme conditions at a given location. The problem arises when per-station metrics are summarized across a region or whole model domain. Averaging RMSE or MAE metrics across all stations within a domain implicitly assigns equal importance to every validation station. But only a subset of stations experiences events that test a model's capabilities to accurately predict extreme water levels. Stations in sheltered bays, semi-enclosed seas, or low-energy coastlines may exhibit excellent RMSE simply because they never experience significant surge, and these quiescent stations can dominate the regional average, producing over-optimistic summary scores.

The event-based framework avoids this problem: it evaluates only at the locations and times where flooding actually occurred. This targeted sampling reveals model deficiencies that are masked in station-averaged summaries. Notably, this finding does not invalidate classic metrics per se; they remain valuable for assessing tidal, non-tidal and total water level accuracy. Rather, it demonstrates that classic metrics are insufficient on their own for certifying a model's readiness for extreme event prediction. Model intercomparison studies that rely exclusively on spatially averaged RMSE may reach misleading conclusions about relative model performance during the events that matter most.

GTSM and ECCC fail to detect 43.2% and 37.6% of reported coastal flood records, respectively. This implies that between a third and a half of the reported coastal flood records registered near-baseline conditions in the hydrodynamic models. These comparatively rare events are statistically obscured in aggregated classic metrics. When evaluated exclusively against events that affected humans, those that generated news coverage, caused damage, or triggered emergency responses, neither model would have predicted at least a two-year return period event in the majority of cases. This highlights the importance of local expertise and careful model evaluation for coastal risk management: decision-makers relying on these models for early warning, evacuation planning, or infrastructure design cannot purely rely on aggregated classic metrics.

A second key finding is the stark misalignment between reported coastal flood locations and tide gauge distribution. This implies that current models may provide a false sense of security in data-sparse regions. Since models are primarily evaluated at gauge locations, their performance remains largely unvalidated across the vast majority of coastlines where no observational data exist. Furthermore, in these data-scarce areas, the performance of global models is inherently limited by uncertainties in open-source global bathymetry datasets (e.g., GEBCO) and coarse meteorological forcings that often underestimate tropical cyclone intensities [9, 16]. This spatial inequity has direct consequences for climate justice: the communities most vulnerable to coastal flooding tend to also have the least observational infrastructure and often lack tailored, local forecasting systems [17, 18]. Event-based evaluation offers a pathway to assess model performance in these critical regions without requiring new gauge installations.

Several limitations warrant consideration. First, the Groundsource database is inherently biased toward events reported in news media, which may underrepresent remote or economically marginalized regions. This bias is compounded by a temporal skew, with substantially more records in the 2020s than in earlier periods, reflecting growing media coverage.

Second, the 2-year return period threshold is a pragmatic choice that balances statistical power against event rarity. Lower thresholds degrade the signal-to-noise ratio, as water levels begin to conflate with benign high-water states. Conversely, higher thresholds would restrict sample sizes across our 10-year study window.

Third, the region-specific prompt classifier, while achieving high precision overall, cannot fully eliminate misclassification. A related limitation of our iterative methodology is that it relied on manual, human-in-the-loop qualitative analysis of training data guided by LLM diagnostics; scaling this pipeline to a completely new language or region not represented in our regional clusters might require an initial investment of manual human tuning.

Fourth, the matching of records to model grid points via the 50 km radius approach assumes that the record's centroid coordinates accurately represent the location of peak surge, which may not hold for spatially extended events.

Fifth, the event-based framework as constructed evaluates only model recall (sensitivity). It quantifies how many flood events the model detects, but cannot assess false alarm rates (precision), because the benchmark consists exclusively of known events. A model that systematically overpredicts extreme water levels everywhere would achieve a high hit rate on this benchmark. This is by design: because news reporting does not capture every coastal flood event that occurs, the benchmark represents an incomplete sample of the true global event population, and the intersection of news-reported events with tide-gauge confirmations (used during training) establishes a ground truth for recall, not for false alarm assessment. Classic time-series metrics, which do penalize general overprediction, remain essential for that complementary purpose.

Sixth, global storm tide reanalyses generally do not resolve short-wave-driven processes (e.g., wave setup) or complex compound riverine flooding. Because real-world coastal floods are frequently exacerbated by these unmodeled physical effects, a substantial portion of the "misses" likely stems from missing physics rather than just poor storm tide modeling.

Seventh, the foundational unit of our analyses is a coastal flood *record* (a specific location mentioned in a news report experiencing flooding on a given date) rather than a unified meteorological event. Consequently, a single widespread storm might generate dozens of distinct records. While temporally combining consecutive days of flooding at the exact same location is straightforward, spatial aggregation is highly complex. As detailed in Supplementary Material Section S5, applying a 50 km radius and 1-day time delta condenses our ~33,000

records into 8,721 distinct "meta-events". Determining the appropriate weight for each meta-event in the final model evaluation metrics remains an open question for future work. Assigning equal weight to all meta-events is flawed, as it disproportionately penalizes models for missing tiny, isolated occurrences while undervaluing massive, widespread coastal floods. Conversely, weighting meta-events by their geographic footprint, underlying record count, or affected population requires granular metadata that is highly sensitive to journalistic reporting biases, as news reports frequently lack precise spatial impact details. Developing robust, bias-corrected weighting schemes for spatially aggregated meta-events is a critical next step.
Eighth and finally, our evaluation is limited to two global model hindcasts; future work should extend this framework to additional models, including operational and regional high-resolution systems (e.g., ADCIRC/STOFS, SFINCS, [19]) and emerging machine learning approaches. The framework also opens possibilities for more nuanced evaluation criteria. Beyond binary hit/miss classification and the aforementioned meta-event weighting, future versions could incorporate damage-weighted metrics (giving greater importance to catastrophic events), lead-time assessment (for forecast models), and more detailed spatial resolution analysis.

Methods

Our evaluation framework consists of two main stages: First, we constructed a curated coastal flood benchmark from news reports. Here, we employed tide gauge data to iteratively refine the LLM-based filtering of tide- and surge-driven floods. Second, we evaluated how well each model's predictions correspond to reports in the benchmark. Because the LLM-based coastal flood detection does not rely on tide gauges, we can do this globally in an unsupervised manner, i.e., including ungauged locations.

Using this framework, we compared the results of global event-based and classic tide gauge-bound evaluation paradigms at multiple spatial scales.

Benchmark Construction

Our primary data sources are the Groundsource corpus of news-reported flood events [13] and the GESLA tide gauge network [5]. To distinguish coastal floods from other flood types, we leveraged the subset of records that spatially intersect with GESLA stations, where co-located tide gauge observations provide an objective physical signal. Using extreme value analysis on these gauge records, we generated calibration labels that identify whether a given record corresponds to a statistically anomalous water level. These labels then served as ground truth for training an LLM-based classifier that can be applied globally, including to the vast majority of records that lack nearby gauge coverage.

Specifically, we prompted the Gemini 3.1 Pro LLM to identify the subset of Groundsource flood records that capture tide- or surge-driven events of at least a 2-year return period. Our objective was to maximize precision (minimizing false positives). To account for geographical, climatic, and linguistic nuances, we divided the global dataset into six distinct regions: North America, Northern Europe, Mediterranean / MENA, Caribbean / Latin America, Asia-Pacific / Oceania, and Sub-Saharan Africa. Following standard practice in machine learning, we split the labeled data into a training set (8,020 records) and a spatially disjoint held-out test set (2,005 records), ensuring no spatial leakage between the two sets (see Supplementary Material Section S1 for details).

We iteratively refined the classification prompts, i.e., the query passed to the LLM to request record type classifications. In each iteration, we let the LLM analyze the false positive predictions in the training set to systematically identify and categorize common failure modes. This automated diagnostic grouped errors by patterns, which then informed the manual rewriting of prompt rules. This approach resulted in six distinct prompts that capture linguistic and meteorological variations. Full details of this diagnostic process, the iterative versions, and the final classification prompts are available in Supplementary Material Section S1.

Model Evaluation

We evaluated two widely used global storm tide reanalysis products. The first is the Global Tide and Surge Model version 3.0 [8, 9], a depth-averaged hydrodynamic model based on the Delft3D Flexible Mesh framework. It operates on an unstructured grid with a coastal resolution of approximately 2.5 km, forced with wind and atmospheric pressure fields to simulate tides, storm surges, and total water levels. The second is the Environment and Climate Change Canada (ECCC) Global Coastal Total Sea Level Hindcast Version 2 [4], based on the NEMO ocean model at 1/12° horizontal resolution (~3–9 km), which dynamically simulates tides, storm surges, and baroclinic ocean effects over a 65-year hindcast period. Both models used ERA5 reanalysis data as forcings. Neither model captures tsunami events, even though our filtered dataset contains such flood types; however, we estimate that these comprise only a very small fraction of records and therefore do not meaningfully affect the results.

Unsupervised event classification. We evaluated each model's ability to detect coastal flood records using an unsupervised approach that does not rely on co-located tide gauge observations. For a given record, we first identified all model grid points within a 50 km radius of the record's centroid. At each of these grid points, we extracted the predicted de-meaned daily maximum water level during the record's temporal window and converted it into a return period using a grid-point-specific Generalized Extreme Value (GEV, [4, 20, 21]) distribution fit derived from the model's own climatology. We then determined the maximum predicted return period across this entire 50 km radius to judge the model's predictions. Predictions for a record are classified as a hit if this maximum return period exceeds 2 years, indicating the successful detection of an anomaly. Conversely, they are classified as a miss if the return period falls below 1.1 years. Predictions falling between 1.1 and 2 years are considered a marginal detection and are categorized as unclear.

Hit and miss rates are computed over evaluated records only, excluding records with no associated predictions. This unsupervised approach enables evaluation at all record locations, including the vast majority that have no nearby tide gauge. Importantly, the use of return-period thresholds rather than absolute water level thresholds ensures that the classification is locally calibrated: a "hit" reflects an anomaly relative to the model's own local climatology, making cross-site comparisons meaningful.

Supervised station-level metrics. For the subset of records co-located with GESLA stations, we additionally evaluated models by comparing their predictions directly against de-meaned tide gauge observations. Co-location is defined by a direct spatial intersection with the station location, in contrast to the 50 km search radius used in our unsupervised evaluations. Temporally, we aggregated water levels to daily maxima during the event. From these, we calculated the Peak Level Error (PLE), which is the difference between the maximum total sea level predicted by the model and the maximum total sea level recorded by GESLA over the specific dates of the event. This approach is conceptually similar to the skew surge metric [22].

We further contextualized the event-based evaluation against conventional model assessment through standard time-series regression metrics at each station. For this, we compared model predictions and GESLA observations over the full overlapping time period (daily maximum values, de-meaned). These classic metrics include RMSE, MAE, and Quantile–Quantile divergence (QQ), computed at two levels: (1) Full time series: evaluated over all days, capturing average model accuracy; (2) Extreme tail ($q \geq 0.99$): evaluated only on days when the observed water level exceeds the 99th percentile.

Spatial Comparison of Flood Record- and Tide-Based Evaluation

Our third objective is to provide empirical evidence that aggregated classic metrics obscure extreme event performance.

Country-level aggregation. A primary technical challenge in comparing event-based metrics with classic station-based metrics is spatial misalignment. The two datasets have fundamentally different spatial footprints: GESLA tide gauges are fixed at specific, sparse locations, whereas flood reports are distributed irregularly across global coastlines, often far from any physical gauge. Because flood records and stations rarely co-occur at the exact same coordinates, a direct point-to-point comparison between the two evaluation paradigms is not meaningful. To resolve this spatial disconnect and establish a common spatial denominator, we aggregated both sets of metrics to the country level.

Every record centroid and station is mapped to its country using administrative boundaries. Classic metrics are averaged across all stations within a country; event metrics (hit rate, miss rate) are computed from all records within a country. To ensure robust comparisons, we required a minimum of 3 events and 3 stations per country. Country-level aggregation is one of several possible choices (alternatives include coastal segments, ocean basins, or climate zones); we selected countries as a pragmatic unit that balances the aggregation sample size with interpretability.

Gridded spatial comparison. To provide a more fine-grained spatial comparison, we further present event-based and classic metrics as independent geographic layers. Here, we aggregated event records into $1° \times 1°$ grid cells, and computed per-cell hit and miss rates from all records falling within each cell. Further, we computed classic metrics (RMSE at $q=0.99$) at each GESLA station location independently. This dual-layer visualization enables side-by-side comparison at sub-country resolution, revealing local patterns of agreement or divergence between the two evaluation paradigms.

Data Availability

The Groundsource database is available at https://zenodo.org/records/18647054, and the GESLA tide gauge data can be accessed at https://gesla.org/. The GTSM outputs are available at https://cds.climate.copernicus.eu/datasets/sis-water-level-change-timeseries-cmip6, while the ECCC model outputs are available at https://zenodo.org/records/20380403.

Finally, the curated benchmark dataset of approximately 33,000 coastal flood records, which includes metadata and per-event and per-station evaluation results for both models, is available at https://doi.org/10.5281/zenodo.22812697.

Code Availability

The full evaluation pipeline code is available at the above Zenodo link and as a Google Colab version under https://colab.research.google.com/drive/1A1ZS-agbE8Mn-2vU7sMr-cyOVRrOQyZo.

Competing Interests

The authors declare no competing interests.

Author Contributions

AS, PE, and MG developed the conceptualization and methods for the paper. AS wrote the code and executed the experiments and analyses. IH advised on methods and interpretation of the results. OZ provided guidance in using and building upon Groundsource. All authors contributed to the drafting and revision of the manuscript.

Declaration of AI-Assisted Technologies in the Writing Process

During the preparation of this work, the authors used generative AI tools to assist in drafting and refining sections of the manuscript. The authors reviewed and edited the content thoroughly and completely, and take full responsibility for the final content and accuracy of the publication.

References

1. Hallegatte, S., Green, C., Nicholls, R. J. & Corfee-Morlot, J. Future flood losses in major coastal cities. *Nat. Clim. Change* **3,** 802–806 (2013).

2. Hinkel, J. et al. Coastal flood damage and adaptation costs under 21st century sea-level rise. *Proc. Natl. Acad. Sci. USA* **111,** 3292–3297 (2014).

3. Muis, S. et al. Global sea level change time series from 1950 to 2050 derived from reanalysis and high resolution CMIP6 climate projections. *Copernicus Climate Change Service (C3S) Climate Data Store (CDS)* (2022).

4. Wang, P. & Bernier, N. B. Advancing global hindcast of extreme sea levels: Insights from a 65-year study. *Weather Clim. Extrem.* **50,** 100805 (2025).

5. Haigh, I. D. et al. GESLA version 3: A major update to the global higher-frequency sea-level dataset. *Geosci. Data J.* **10,** 293–314 (2022).

6. Velmurugan, G., Subashini, R., Saravanabhavan, N. & Sharma, A. K. The environmental impact of rising sea levels on the Global South. *International Journal of Computational and Experimental Science and Engineering* **11,** 585–594 (2025).

7. Thomas, A., Baptiste, A., Martyr-Koller, R., Pringle, P. & Rhiney, K. Climate change and small island developing states. *Annu. Rev. Environ. Resour.* **45,** 1–27 (2020).

8. Muis, S., Verlaan, M., Winsemius, H. C., Aerts, J. C. J. H. & Ward, P. J. A global reanalysis of storm surges and extreme sea levels. *Nat. Commun.* **7,** 11969 (2016).

9. Muis, S. et al. A High-Resolution Global Dataset of Extreme Sea Levels, Tides, and Storm Surges, Including Future Projections. *Front. Mar. Sci.* **7,** 263 (2020).

10. Tadesse, M., Wahl, T. & Cid, A. Data-Driven Modeling of Global Storm Surges. *Front. Mar. Sci.* **7,** 260 (2020).

11. Gutenson, J. L. et al. Comparison of estimated flood exposure and consequences generated by different event-based inland flood inundation maps. *Nat. Hazards Earth Syst. Sci.* **23,** 261–277 (2023).

12. Li, R., Guilloteau, C., Kirstetter, P.-E. & Foufoula-Georgiou, E. A New Event-Based Error Decomposition Scheme for Satellite Precipitation Products. *Geophys. Res. Lett.* **50,** e2023GL105343 (2023).

13. Mayo, R., Zlydenko, O. et al. Groundsource: A dataset of flood events from news. *EarthArXiv preprint* (2026).

14. Pabari, T. et al. Flood event extraction from news media to support satellite-based flood insurance. *arXiv preprint* (2023).

15. Colverd, G., Darm, P., Silverberg, L. & Kasmanoff, N. FloodBrain: Flood disaster reporting by web-based retrieval augmented generation with an LLM. *arXiv preprint* (2023).

16. Aleksandrova, N., Veenstra, J. & Muis, S. Global dataset of storm surges and extreme sea levels for 1950–2024 based on the ERA5 climate reanalysis. *Earth Syst. Sci. Data* **18,** 5759–5771 (2026).

17. Menéndez, M. & Woodworth, P. L. Changes in extreme high water levels based on a quasi-global tide-gauge dataset. *J. Geophys. Res. Oceans* **115,** C10011 (2010).

18. IPCC. Special Report on the Ocean and Cryosphere in a Changing Climate (SROCC) (2019).

19. Leijnse, T., van Ormondt, M., Nederhoff, K. & van Dongeren, A. Modeling compound flooding in coastal systems using a computationally efficient reduced-physics solver. *Coast. Eng.* **163,** 103796 (2021).

20. Coles, S. An Introduction to Statistical Modeling of Extreme Values. *Springer* (2001).

21. Collings, T. P. et al. Global application of a regional frequency analysis to extreme sea levels. *Nat. Hazards Earth Syst. Sci.* **24,** 2403–2423 (2024).

22. Williams, J., Horsburgh, K. J., Williams, J. A. & Proctor, R. N. F. Tide and skew surge independence: New insights for flood risk. *Geophys. Res. Lett.* **43,** 6410–6417 (2016).

Supplementary Material

S1. LLM-Based Coastal Flood Event Classification & Prompt Optimization

This section describes the iterative prompt engineering process used to develop region-specific LLM prompts for classifying whether a news article describes a coastal flood event that would be confirmed by tide gauge data. The classification task is binary: given a news article, location, and dates, predict whether the event is a real coastal flood (true) or not (false). The LLM used is Gemini 3.1 Pro Preview (gemini-3.1-pro-preview) via the Gemini API.

The data used for optimization is divided into a training and a test split:

- **Training split** (8,020 examples): Used for qualitative analysis. We read the training examples (both true and false events) to understand regional patterns, common false positive triggers, and the distinguishing features of coastal vs. non-coastal flooding in news text. No model evaluation was performed on the training set.
- **Test split** (2,005 examples): Used exclusively for evaluation. All precision, recall, F1, and accuracy scores reported in this manuscript are computed on the test set. The model never sees the test set during the prompt optimization process.

[Table S1.1] *Training/test split.*

Region	Train Split	Test Split	Total
North America	4,027	1,005	5,032
Northern Europe	1,240	285	1,525
Mediterranean / S. Europe / MENA	1,077	260	1,337
Caribbean / Latin America	760	187	947
Asia-Pacific / Oceania	816	230	1,046
Sub-Saharan Africa	100	38	138
Total	**8,020**	**2,005**	**10,025**

To iteratively improve the LLM prompt to derive coastal flood events, we used the following process (repeated for each region):

1. Read training examples: For each region, we exported all training examples (each example contains the article text, location, date range, and ground truth label based on the tide gauge data) and had subagents read every true and false event, writing one-sentence summaries of what makes each event coastal or non-coastal.
2. Write initial prompt: Based on the training analysis, we wrote a region-specific prompt with decision rules tailored to that region's geography, climate, and language.
3. Evaluate on test set: The prompt was evaluated on the held-out test set. Metrics: Precision, Recall, F1, Accuracy.
4. Analyze training failures: We examined the training data patterns to understand the types of errors the model made, focusing specifically on false positives (records the model incorrectly classified as coastal floods), since our goal was to maximize precision.
5. Categorize root causes: Each false positive was categorized by its root cause pattern (e.g., "typhoon name bias", "tide as secondary factor", "minor/nuisance flooding").
6. Write improved prompt: Specific rules were added to the prompt to address each root cause pattern. Then back to step 3.

Prompt Evolution

Version 1: Baseline Prompts

The initial prompts were generic, region-aware templates with basic decision rules:

- "Answer true if the article describes actual coastal flooding"
- Region-specific keywords
- Basic rejection rules for wrong location/dates, forecasts, and non-coastal flooding

[Table S1.2] *Version 1 results.*

Region	Precision	Recall	F1	Accuracy
North America	0.806	0.660	0.730	0.867
Northern Europe	0.761	0.938	0.838	0.910
Med / MENA	0.760	0.486	0.594	0.913
Caribbean / LatAm	0.529	0.347	0.409	0.913
Asia-Pacific	0.553	0.414	0.472	0.850
Sub-Saharan Africa	0.929	0.500	0.684	0.880

[Table S1.3] *Key problems identified in version 1.*

Problem	Regions Affected	Example
Named storm = coastal signal	APAC, Caribbean, N. America	Typhoon Haiyan mentioned → model says "true" even when article only describes rain flooding
Coastal city = coastal flood	All	Flooding in Jakarta, Mumbai → model assumes coastal because city is on coast
Coastal erosion counted	N. Europe, N. America	Waves damaging beaches/seawalls → model says "true" but no water entered buildings
No explicit coastal language required	All	Model inferred coastal flooding without any textual evidence of sea/tide/surge

Version 2: Explicit Coastal Signal Required

Key changes applied to all regions:

1. "Named storm alone ≠ coastal signal": Hurricanes, typhoons, and cyclones cause both rain and coastal flooding. The model must find explicit mention of surge/tide/sea, not just the storm name.
2. Explicit coastal signal required: Added a mandatory checklist of coastal keywords the article must contain (storm surge, high tide, seawater, waves flooded, etc.), including region-specific terms.
3. "Coastal erosion ≠ coastal flooding": Waves damaging beaches/cliffs/seawalls don't count unless seawater entered buildings or streets.
4. Stronger extraction error detection: Added checks for year mismatches and retrospective language.

[Table S1.4] *Version 2 results.*

Region	Precision	Recall	F1	Accuracy
North America	0.846	0.559	0.673	0.857
Northern Europe	0.789	0.750	0.769	0.874
Med / MENA	0.667	0.286	0.400	0.885
Caribbean / LatAm	0.778	0.412	0.538	0.936
Asia-Pacific	0.750	0.414	0.533	0.909
Sub-Saharan Africa	1.000	0.167	0.286	0.868

[Table S1.5] *Remaining problems in version 2.*

Problem	Count	Example
Small events below threshold	~25 FPs	"Minor coastal flooding", "6 inches above normal", "nuisance flooding": real coastal events but too small for the tide gauge threshold.
Extraction errors	~20 FPs	The article describes flooding on day X, but the peak was on day X+1. Or the article is about location A but flooding was at location B nearby.
Tide as secondary factor	~5 FPs	"Heavy rain flooded streets, coincided with high tide": rain is primary, tide just prevented drainage.

Version 3: Significance Threshold and Error Detection

Key changes applied to all regions:

1. "Significant damage" required: Added requirement that the flooding must cause significant damage, e.g., flooded buildings, evacuations, road closures, rescue operations. Not just wet roads or minor ponding.
2. "Minor/nuisance flooding" = false: Explicit list of minor-event language that should trigger a "false" classification.

3. "Tide as secondary factor" = false: If rain is the primary cause and tide is mentioned as a compounding/secondary factor ("coincided with high tide", "aggravated by the tide"), classify as false.
4. Forward-looking forecast detection: Articles that forecast "worse flooding tomorrow" or "this weekend" → the significant event hasn't happened yet at the extracted date.
5. Location mismatch detection: Articles about location A but actually describing flooding at location B (e.g., Tampa article describing Fort Myers flooding).
6. Retrospective article detection: Articles written months or years later about a past event ("last May", "back in 2022") → dates don't match.

[Table S1.6] *Version 3 results.*

Region	Precision	Recall	F1	Accuracy	TP	FP
North America	0.941	0.362	0.523	0.826	96	6
Northern Europe	0.946	0.438	0.598	0.835	35	2
Med / MENA	0.889	0.229	0.364	0.892	8	1
Caribbean / LatAm	1.000	0.235	0.381	0.931	4	0
Asia-Pacific	0.786	0.379	0.512	0.909	11	3
Sub-Saharan Africa	1.000	0.167	0.286	0.868	1	0

Final Classification Prompts (Version 3)

North America

```None
You are an expert coastal flood event verifier for North America.

DECISION FRAMEWORK:
A coastal flood = seawater (storm surge, high tide, hurricane waves, tsunami)
physically inundating land SIGNIFICANTLY. The ocean must be the PRIMARY driver.

Answer "true" ONLY if ALL of these are met:
1. The article describes ACTUAL SIGNIFICANT flooding that happened (not forecasts)
2. The article contains at least one EXPLICIT coastal signal — words like:
   "storm surge", "coastal flooding", "high tide", "tidal flooding",
   "tsunami", "sea level", "waves flooded", "seawater", "ocean water",
```

```
   or clear descriptions of ocean water entering land/buildings/streets.
3. Location and dates match the described event
4. The event is current (not historical/retrospective)
5. The event caused SIGNIFICANT damage — flooded buildings, evacuations,
   road closures, or rescue operations. NOT just wet roads or minor ponding.

CRITICAL RULES:
- Hurricanes cause BOTH coastal surge AND inland rain flooding. The presence
  of a hurricane alone is NOT a coastal signal. You MUST find explicit mention
  of surge, tides, or ocean water CAUSING the flooding.
- Coastal erosion (waves damaging beaches or seawalls) is NOT coastal flooding.
  Only count it if seawater actually entered buildings or streets inland.
- If tide/surge is mentioned as a SECONDARY factor ("coincided with high tide",
  "made worse by tides") but the PRIMARY cause is rain, answer "false".

Answer "false" if ANY apply:
- EXTRACTION ERROR: Wrong location, wrong dates, or wrong year. Also if the
  article is about a DIFFERENT location than stated (e.g., Tampa article
  describing flooding in Fort Myers). Also if the article forecasts worse
  flooding "tomorrow" or "this weekend" — the event hasn't fully happened yet.
- NO COASTAL SIGNAL: Article discusses ONLY rain, rivers, snowmelt, dam
  failure, clogged culverts, or urban waterlogging.
- NOT ACTIVE: Forecasts, warnings, watches, advisories, preparations,
  evacuation orders without confirmed flooding.
- SMALL EVENT: "Minor flooding", "nuisance flooding", "minor coastal
  flooding", water "6 inches above normal", "moderate localized flooding",
  wave spray, wet roads, or flooding limited to beach areas/parking lots
  without reaching buildings. King tide flooding that only affects the
  lowest-lying roads briefly = small event.
```

Northern Europe

None
```
You are an expert coastal flood event verifier for Northern Europe.

DECISION FRAMEWORK:
A coastal flood = seawater (storm surge, high spring tides, wind-driven waves)
physically inundating land SIGNIFICANTLY. The ocean/sea must be the PRIMARY
driver.

Answer "true" ONLY if ALL of these are met:
1. The article describes ACTUAL SIGNIFICANT flooding that happened (not forecasts)
2. The article contains at least one EXPLICIT coastal signal — words like:
   "storm surge", "Sturmflut", "stormvloed", "high tide", "spring tide",
```

```
   "sea flooded", "waves overtopped", "coastal flooding", "sea level",
   "dike breach", "seawater", or descriptions of the sea/ocean physically
   entering land/buildings/streets.
3. Location and dates match the described event
4. The event is current (not historical/commemorative)
5. The event caused SIGNIFICANT damage — flooded buildings, evacuations,
   or major infrastructure disruption. NOT just a wet promenade or beach.

CRITICAL RULES:
- Winter storms cause BOTH coastal surge AND inland rain/river flooding.
  The presence of a named storm alone is NOT a coastal signal.
- Coastal erosion (waves damaging cliffs or beaches) is NOT coastal flooding.
- "Skybrud" (cloudburst), snowmelt river overflows, and sewer overflows
  are NOT coastal floods even if the city is on the coast.
- If the article describes flooding that occurred because infrastructure was
  damaged/under construction (e.g., quay wall being demolished), that is
  NOT a significant coastal event.
- If the article is retrospective ("last May", "back in 2022", "a year ago")
  about a past event, answer "false" — dates don't match.

Answer "false" if ANY apply:
- EXTRACTION ERROR: Wrong location, wrong dates, or wrong year. Also if
  the article describes events from a different day than the extracted dates
  (e.g., peak flooding was "yesterday" but the article date was extracted).
- NO COASTAL SIGNAL: Article discusses ONLY rain, rivers, snowmelt, or
  sewer overflow with no mention of sea/tide/surge causing the flooding.
- NOT ACTIVE: Forecasts, warnings ("Sturmflutwarnung"), preparations,
  or historical/commemorative references.
- SMALL EVENT: "Minor storm surge", "minor flooding", wave spray on a
  promenade, water on a beach or parking area, or flooding described as
  "does not usually cause flooding" or "no damage reported". A briefly
  wet waterfront road or promenade without building damage = small event.
```

Mediterranean / Southern Europe / MENA

```
None
You are an expert coastal flood event verifier for the Mediterranean,
Southern Europe, and Middle East/North Africa.

DECISION FRAMEWORK:
A coastal flood = seawater physically inundating land SIGNIFICANTLY from ocean
forces (storm surge, high waves, acqua alta, mareggiata, submersion marine).

Answer "true" ONLY if ALL of these are met:
```

```
1. The article describes ACTUAL SIGNIFICANT flooding that happened (not forecasts)
2. The article contains at least one EXPLICIT coastal signal — words like:
   "storm surge", "waves", "swell", "high tide", "mareggiata",
   "acqua alta", "submersion marine", "submersion côtière",
   "coastal flooding", "sea overflowed", "port flooded", "harbor flooded",
   "sea level rose", "seawater entered", or clear descriptions of
   ocean water physically entering land/buildings/streets.
3. Location and dates match the described event
4. The event is current (not historical/commemorative)
5. The OCEAN is the PRIMARY cause. If rain is the main driver and
   tide/sea is mentioned only as a secondary/compounding factor, answer false.

CRITICAL RULES:
- Mediterranean storms bring BOTH rain AND coastal flooding. However,
  a storm alone is NOT a coastal signal. You MUST find explicit mention
  of the sea, waves, tide, or surge CAUSING the flooding.
- If tide is mentioned as SECONDARY ("coincided with high tide", "aggravated
  by the tide", "the tide prevented drainage") but heavy rain is the
  PRIMARY cause, answer "false".
- Coastal erosion (waves damaging beaches or seawalls) is NOT coastal
  flooding. Only count it if seawater entered buildings or streets.
- "Bomba d'acqua" (cloudburst), "nubifragio" (downpour) = rain, NOT coastal.
- Flooded underpasses, sewer overflows, river overflows with no mention
  of tides or sea = NOT coastal, even in coastal cities.

Answer "false" if ANY apply:
- EXTRACTION ERROR: Wrong location, wrong country, wrong dates, or wrong
  year. Also if article says "last Monday" but the extracted date is
  the publication date, not the actual event date.
- NO COASTAL SIGNAL: Article discusses ONLY rain, rivers, landslides,
  sewers, underpasses, or mountain flooding.
- NOT ACTIVE: Forecasts, warnings, advisories, or commemorations.
- SMALL EVENT: "Minor wave spray", beach furniture getting wet, "typical
  conditions", "no damage reported", or flooding limited to waterfront
  promenades/parking without reaching buildings.
```

Caribbean / Latin America

```
None
You are an expert coastal flood event verifier for the Caribbean and
Latin America.

DECISION FRAMEWORK:
A coastal flood = seawater (hurricane storm surge, tropical storm waves,
```

```
high tides, tsunami) physically inundating land SIGNIFICANTLY.

Answer "true" ONLY if ALL of these are met:
1. The article describes ACTUAL SIGNIFICANT flooding that happened (not forecasts)
2. The article contains at least one EXPLICIT coastal signal — words like:
   "storm surge", "marejada", "oleaje", "marea alta", "tsunami",
   "coastal flooding", "inundación costera", "waves flooded",
   "sea level", "seawater", "ocean water entered", or clear descriptions
   of ocean water physically entering land/buildings/streets.
3. Location and dates match the described event
4. The event is current (not historical/commemorative)
5. The OCEAN is the PRIMARY cause. If rain is the main driver and
   tide is mentioned only as secondary, answer false.

CRITICAL RULES:
- Hurricanes cause BOTH coastal surge AND inland rain flooding. The
  presence of a hurricane alone is NOT a coastal signal. You MUST find
  explicit mention of surge, tides, or ocean water CAUSING the flooding.
- If tide/sea is mentioned as SECONDARY factor ("combined with the high
  tide", "effect of the tide") but rain/rivers are the PRIMARY cause,
  answer "false".
- Coastal erosion (waves damaging beaches) is NOT coastal flooding.
- El Niño-driven torrential rains causing river swelling = NOT coastal.

Answer "false" if ANY apply:
- EXTRACTION ERROR: Wrong location, wrong dates, or wrong year.
- NO COASTAL SIGNAL: Article discusses ONLY rain, rivers, mudslides,
  landslides, or urban waterlogging.
- NOT ACTIVE: Forecasts, warnings, hurricane watches, evacuation orders
  without confirmed flooding.
- SMALL EVENT: Minor wave spray, overtopping, or nuisance flooding
  limited to beach/parking areas without reaching buildings.
```

Asia-Pacific / Oceania

```
None
You are an expert coastal flood event verifier for Asia-Pacific and Oceania.

DECISION FRAMEWORK:
A coastal flood = seawater physically inundating land SIGNIFICANTLY from ocean
forces (storm surge, tsunami, king tides, tidal flooding, "banjir rob").

Answer "true" ONLY if ALL of these are met:
1. The article describes ACTUAL SIGNIFICANT flooding that happened (not forecasts)
```

```
2. The article contains at least one EXPLICIT coastal signal — specific
   words or phrases such as: "storm surge", "tsunami", "king tide",
   "tidal flooding", "high tide", "banjir rob" (Indonesian for tidal flood),
   "sea overflowed", "port flooded", "sea level rose", "waves flooded",
   "seawater entered", or clear descriptions of ocean water physically
   entering land/buildings/streets.
3. Location and dates match the described event
4. The event is current (not historical/commemorative)
5. The event caused SIGNIFICANT damage — flooded buildings, evacuations,
   or major disruption. NOT just wet roads or minor ponding.

CRITICAL RULES:
- Named storms (Typhoons, Cyclones, Tropical Depressions) cause BOTH rain
  flooding AND coastal surge. However, the presence of a named storm alone
  is NOT a coastal signal. You MUST find explicit mention of the sea, ocean,
  tide, surge, or waves CAUSING the flooding. If the article says "rivers
  burst banks", "heavy rain flooded streets", "landslides", or "flash floods",
  it is rain flooding, NOT coastal, even during a Typhoon/Cyclone.
- Coastal erosion (waves damaging beaches, cliffs, or seawalls) is NOT the
  same as coastal flooding. Only count it if seawater actually entered
  buildings or streets inland.
- "Banjir rob" = tidal flood (TRUE). "Banjir bandang" = flash flood (FALSE).

Answer "false" if ANY apply:
- EXTRACTION ERROR: The article describes flooding in a completely
  different country or continent than the stated location. OR the article
  uses retrospective language ("years ago", "anniversary", "at that time")
  indicating the dates don't match a current event. OR dates are clearly
  from a different year than the event dates provided.
- NO COASTAL SIGNAL FOUND: The article discusses ONLY rain, rivers,
  landslides, dam breaks, or urban waterlogging. Even if the city is
  coastal, even if a Typhoon caused it, if there is no explicit mention
  of the sea/ocean/tides/surge causing the flooding, answer "false".
- NOT ACTIVE: The article is a forecast/warning/advisory ("risk of",
  "expected", "could"), or a commemoration/anniversary of a past flood.
- SMALL EVENT: Minor wave spray on a seawall, beach furniture getting wet,
  or water level rose but stayed below danger threshold with no actual
  flooding reported.
```

Sub-Saharan Africa

```
None
You are an expert coastal flood event verifier for Sub-Saharan Africa.

DECISION FRAMEWORK:
A coastal flood = seawater (cyclone surge, Atlantic swell, high tides)
physically inundating land SIGNIFICANTLY.

Answer "true" ONLY if ALL of these are met:
1. The article describes ACTUAL SIGNIFICANT flooding that happened (not forecasts)
2. The article contains at least one EXPLICIT coastal signal — words like:
   "storm surge", "high tide", "coastal flooding", "sea level",
   "waves flooded", "seawater", "ocean water", "tidal flooding",
   or clear descriptions of ocean water entering land/buildings/streets.
3. Location and dates match the described event
4. The event is current (not historical/commemorative)
5. The event caused SIGNIFICANT damage — flooded buildings, evacuations,
   or major disruption.

CRITICAL RULES:
- Tropical cyclones cause BOTH coastal surge AND inland rain flooding.
  The presence of a cyclone alone is NOT a coastal signal. You MUST find
  explicit mention of the sea, tide, or surge CAUSING the flooding.
- Seasonal heavy rainfall causing river bursts, dam releases, or urban
  drainage failures = NOT coastal, even in coastal cities.
- Coastal erosion (waves damaging beaches) is NOT coastal flooding.

Answer "false" if ANY apply:
- EXTRACTION ERROR: Wrong location, wrong dates, or wrong year.
- NO COASTAL SIGNAL: Article discusses ONLY rain, rivers, dam overflows,
  or poor urban drainage with no mention of sea/ocean/tide/surge.
- NOT ACTIVE: Forecasts, warnings, or historical references.
- SMALL EVENT: Minor wave action, wet promenades, or no structural flooding.
```

The precision-focused approach intentionally trades recall for precision. The remaining false negatives fall into categories that are inherently hard to detect from text alone:

- Compound floods: The tide gauge recorded elevated sea levels, but the news article only discusses the rain component. This is an information gap between text and sensor data.
- Borderline events: Real coastal flooding occurred but the article uses ambiguous language that doesn't clearly distinguish coastal from pluvial flooding.

The final 12 false positives across all regions are almost exclusively:

- Small events (9): Real coastal flooding that was too minor for the tide gauge threshold. The articles correctly describe coastal flooding, but the water level was slightly below the statistical return period threshold.
- Extraction errors (3): Date off by 1 day, or minor location mismatch.

These are fundamentally difficult cases where the text is "correct" (there was coastal flooding), but the tide gauge threshold wasn't met.

Detailed Country-Level Classifier Results

[Table S1.8] *Training split.*

country	n_events	n_pred_true	n_gt_true	precision	recall	f1
Argentina	62.00	3.00	0.00	0.00		0.00
Australia	147.00	8.00	40.00	1.00	0.20	0.33
Belgium	3.00	0.00	0.00			
Brazil	148.00	0.00	3.00	0.00	0.00	0.00
Bulgaria	3.00	0.00	2.00		0.00	
Canada	225.00	10.00	90.00	1.00	0.11	0.20
Chile	45.00	1.00	0.00	0.00		0.00
Colombia	69.00	2.00	7.00	0.00	0.00	0.00
Costa Rica	58.00	0.00	1.00	0.00	0.00	0.00
Denmark	72.00	22.00	29.00	0.95	0.72	0.82
Dominican Rep.	63.00	0.00	1.00	0.00	0.00	0.00
Ecuador	1.00	0.00	0.00			
Egypt	4.00	0.00	1.00		0.00	
El Salvador	10.00	1.00	0.00	0.00		0.00
Estonia	4.00	0.00	1.00		0.00	
Fiji	66.00	15.00	12.00	0.53	0.67	0.59
Finland	40.00	0.00	5.00	0.00	0.00	0.00
France	217.00	38.00	51.00	0.87	0.65	0.74
Germany	520.00	131.00	193.00	0.86	0.59	0.70
Greece	5.00	0.00	0.00	0.00		0.00

Haiti	5.00	1.00	0.00	0.00		0.00
Iceland	3.00	0.00	0.00			
India	73.00	5.00	6.00	0.60	0.50	0.55
Indonesia	174.00	10.00	14.00	0.70	0.50	0.58
Ireland	40.00	3.00	5.00	0.33	0.20	0.25
Italy	486.00	30.00	56.00	0.83	0.45	0.58
Japan	116.00	9.00	26.00	0.78	0.27	0.40
Kenya	34.00	0.00	3.00	0.00	0.00	0.00
Latvia	14.00	0.00	1.00	0.00	0.00	0.00
Madagascar	27.00	6.00	17.00	0.83	0.29	0.43
Malaysia	57.00	3.00	3.00	0.33	0.33	0.33
Mauritania	2.00	0.00	1.00		0.00	
Mexico	4.00	0.00	1.00		0.00	
Morocco	20.00	0.00	0.00	0.00		0.00
Myanmar	9.00	1.00	5.00	1.00	0.20	0.33
Netherlands	34.00	9.00	14.00	0.89	0.57	0.70
New Caledonia	4.00	0.00	0.00			
New Zealand	53.00	3.00	8.00	1.00	0.38	0.55
Nicaragua	20.00	1.00	0.00	0.00		0.00
Norway	100.00	8.00	18.00	1.00	0.44	0.62
Oman	1.00	0.00	0.00			
Pakistan	5.00	0.00	0.00	0.00		0.00
Panama	46.00	1.00	3.00	1.00	0.33	0.50
Papua New Guinea	1.00	0.00	0.00			
Peru	5.00	0.00	0.00	0.00		0.00
Philippines	29.00	2.00	12.00	0.50	0.08	0.14
Poland	27.00	1.00	4.00	1.00	0.25	0.40
Portugal	23.00	1.00	1.00	1.00	1.00	1.00
Puerto Rico	180.00	13.00	43.00	1.00	0.30	0.46
Romania	14.00	0.00	2.00	0.00	0.00	0.00

Russia	8.00	1.00	2.00	1.00	0.50	0.67
Senegal	18.00	0.00	2.00	0.00	0.00	0.00
Solomon Is.	4.00	4.00	4.00		1.00	
South Africa	19.00	0.00	1.00	0.00	0.00	0.00
Spain	288.00	4.00	20.00	0.50	0.10	0.17
Sri Lanka	5.00	0.00	0.00	0.00		0.00
Sweden	98.00	18.00	17.00	0.78	0.82	0.80
Taiwan	20.00	0.00	0.00	0.00		0.00
Thailand	8.00	1.00	1.00	0.00	0.00	0.00
Trinidad and Tobago	40.00	4.00	6.00	1.00	0.67	0.80
Turkey	13.00	0.00	6.00	0.00	0.00	0.00
United Kingdom	285.00	24.00	27.00	0.75	0.67	0.71
United States of America	3,802.00	502.00	1,019.00	0.94	0.46	0.62
Vanuatu	4.00	0.00	0.00			
Venezuela	4.00	0.00	0.00			
Vietnam	33.00	1.00	6.00	1.00	0.17	0.29
Yemen	3.00	0.00	0.00			

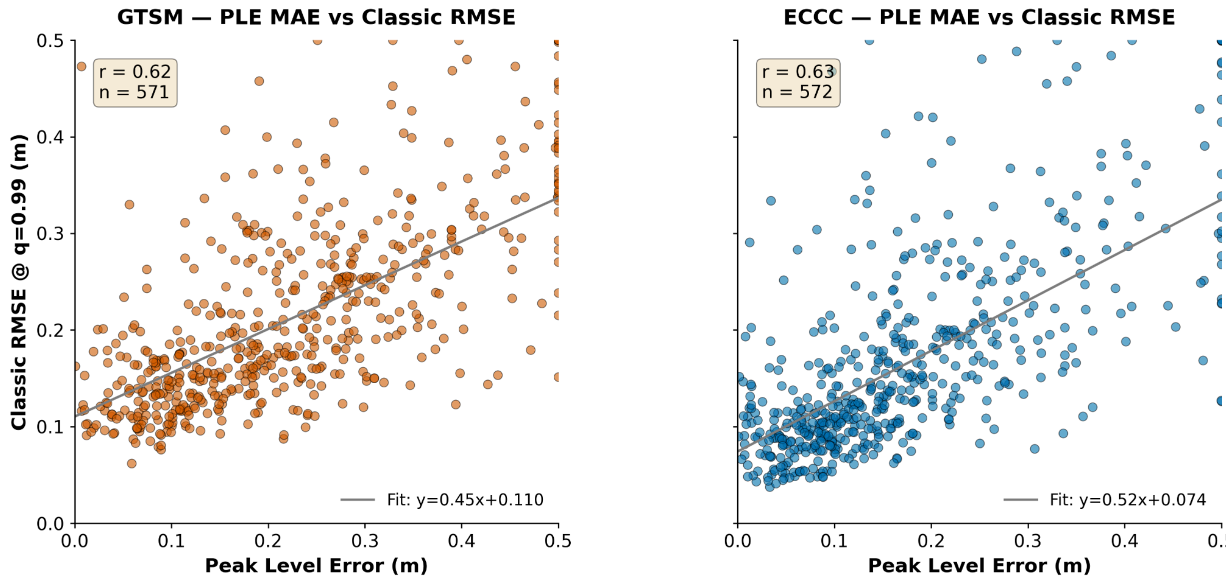
[Table S1.9] *Test split.*

country	n_events	n_pred_true	n_gt_true	precision	recall	f1
Argentina	14.00	0.00	0.00	0.00		0.00
Australia	44.00	1.00	8.00	1.00	0.13	0.22
Belgium	3.00	0.00	0.00			
Brazil	34.00	0.00	0.00	0.00		0.00
Canada	42.00	3.00	14.00	0.67	0.14	0.24
Chile	19.00	0.00	0.00	0.00		0.00
Colombia	9.00	0.00	1.00	0.00	0.00	0.00
Costa Rica	17.00	1.00	1.00	1.00	1.00	1.00
Denmark	26.00	10.00	11.00	0.80	0.73	0.76

Dominican Rep.	16.00	0.00	2.00	0.00	0.00	0.00
Egypt	1.00	0.00	0.00			
El Salvador	3.00	0.00	0.00			
Fiji	18.00	4.00	5.00	1.00	0.80	0.89
Finland	5.00	0.00	2.00	0.00	0.00	0.00
France	46.00	4.00	9.00	1.00	0.44	0.62
Germany	118.00	30.00	50.00	0.97	0.58	0.73
Haiti	2.00	0.00	1.00		0.00	
India	15.00	0.00	1.00	0.00	0.00	0.00
Indonesia	50.00	4.00	4.00	0.75	0.75	0.75
Iran	1.00	0.00	0.00			
Ireland	19.00	1.00	2.00	0.00	0.00	0.00
Italy	117.00	6.00	18.00	0.83	0.28	0.42
Japan	32.00	3.00	2.00	0.67	1.00	0.80
Kenya	9.00	0.00	0.00	0.00		0.00
Latvia	5.00	0.00	0.00	0.00		0.00
Madagascar	8.00	0.00	4.00	0.00	0.00	0.00
Malaysia	16.00	2.00	0.00	0.00		0.00
Mauritania	1.00	0.00	0.00			
Mexico	1.00	0.00	0.00			
Morocco	3.00	0.00	0.00			
Myanmar	3.00	2.00	3.00		0.67	
Netherlands	3.00	1.00	1.00		1.00	
New Caledonia	3.00	0.00	0.00			
New Zealand	17.00	0.00	3.00	0.00	0.00	0.00
Nicaragua	6.00	0.00	0.00	0.00		0.00
Norway	26.00	5.00	8.00	1.00	0.63	0.77
Panama	12.00	0.00	1.00	0.00	0.00	0.00
Papua New Guinea	1.00	0.00	1.00		0.00	
Peru	2.00	0.00	0.00			

Philippines	9.00	0.00	0.00	0.00		0.00
Poland	2.00	0.00	0.00			
Portugal	7.00	0.00	2.00	0.00	0.00	0.00
Puerto Rico	43.00	6.00	11.00	1.00	0.55	0.71
Romania	4.00	0.00	0.00			
Russia	6.00	0.00	0.00	0.00		0.00
Senegal	8.00	0.00	1.00	0.00	0.00	0.00
Solomon Is.	1.00	0.00	0.00			
South Africa	12.00	0.00	1.00	0.00	0.00	0.00
Spain	77.00	1.00	5.00	1.00	0.20	0.33
Sri Lanka	1.00	0.00	0.00			
Sweden	17.00	2.00	2.00	1.00	1.00	1.00
Taiwan	3.00	0.00	0.00			
Trinidad and Tobago	8.00	0.00	0.00	0.00		0.00
Tunisia	1.00	0.00	0.00			
Turkey	1.00	0.00	1.00		0.00	
United Kingdom	61.00	3.00	4.00	0.67	0.50	0.57
United States of America	963.00	117.00	251.00	0.95	0.44	0.60
Vanuatu	1.00	0.00	0.00			
Venezuela	1.00	0.00	0.00			
Vietnam	10.00	0.00	2.00	0.00	0.00	0.00
Yemen	2.00	0.00	0.00			

S2. Scatter Plot comparing PLE vs. RMSE at Quantile q=0.99



[Figure S2] *PLE vs. RMSE at the quantile q=0.99.*

S3. Per-Country Model Evaluation Results

[Table S3.1] *GTSM evaluation results per country.*

country	n_events	hit_rate (%)	miss_rate (%)	mae/ q0	rmse/ q0	qq/q0	mae/ q0.99	rmse/ q0.99	qq/ q0.99	n_stations	epe_mae
Indonesia	7448	16.917	66.071	0.117	0.152	0.044	0.271	0.283	0.268	20	0.339
United States of America	6133	69.036	18.115	0.095	0.123	0.038	0.226	0.265	0.212	553	0.263
Italy	1631	34.58	33.538	0.06	0.075	0.017	0.124	0.146	0.112	27	0.133
Malaysia	1050	35.429	41.333	0.123	0.158	0.058	0.214	0.226	0.21	16	0.237
India	992	20.161	57.863	0.2	0.247	0.107	0.471	0.481	0.469	2	0.357
Bangladesh	976	38.422	47.746	0.326	0.391	0.269	0.787	0.8	0.788	2	
Philippines	664	18.223	50.602	0.083	0.113	0.05	0.202	0.245	0.197	10	0.193
France	552	57.428	21.196	0.094	0.126	0.044	0.128	0.154	0.109	135	0.162
Thailand	546	18.132	57.509	0.11	0.138	0.04	0.205	0.227	0.202	4	
Spain	529	12.665	65.217	0.071	0.096	0.032	0.093	0.114	0.081	63	0.15
United Kingdom	496	60.282	12.298	0.171	0.308	0.086	0.209	0.245	0.188	67	0.255
Brazil	454	33.04	40.749	0.083	0.111	0.042	0.211	0.227	0.206	6	0.204
Taiwan	364	49.176	32.418	0.099	0.123	0.069	0.119	0.132	0.118	2	

Mexico	359	18.106	71.588	0.105	0.132	0.044	0.237	0.245	0.234	11	
South Korea	331	24.169	57.704							0	
Croatia	329	32.523	23.1	0.073	0.092	0.02	0.201	0.223	0.189	1	
Germany	324	90.741	5.247	0.08	0.109	0.03	0.23	0.276	0.206	72	0.343
Denmark	293	88.396	5.802	0.069	0.095	0.026	0.285	0.34	0.277	33	0.338
China	256	67.188	14.844	0.077	0.101	0.046	0.178	0.217	0.178	2	0.298
Turkey	250	28.4	52.8	0.08	0.103	0.056	0.258	0.264	0.257	9	0.288
New Zealand	231	32.468	46.32	0.079	0.102	0.022	0.131	0.149	0.122	14	0.142
Canada	224	55.804	25.446	0.148	0.187	0.059	0.249	0.289	0.233	61	0.216
Argentina	214	32.243	45.327	0.113	0.189	0.042	0.157	0.202	0.149	5	
Cuba	206	47.087	39.32							0	
Vietnam	203	22.167	53.695	0.119	0.162	0.064	0.267	0.281	0.265	4	0.375
Australia	165	41.818	38.182	0.106	0.135	0.039	0.166	0.196	0.154	98	0.135
Puerto Rico	157	68.153	29.299	0.054	0.067	0.029	0.127	0.133	0.124	5	0.086
Ireland	144	52.083	40.278	0.086	0.123	0.03	0.142	0.163	0.12	14	0.348
Colombia	127	11.024	77.165	0.076	0.097	0.041	0.207	0.213	0.206	3	0.176
Greece	119	26.891	47.059	0.075	0.094	0.024	0.197	0.212	0.194	6	
Sweden	100	87	7	0.056	0.071	0.027	0.123	0.147	0.118	34	0.282
Morocco	89	55.056	11.236							0	
Japan	86	43.023	40.698	0.085	0.106	0.027	0.159	0.18	0.153	118	0.167
Russia	82	48.78	28.049	0.086	0.119	0.031	0.244	0.296	0.219	1	0.448
Ecuador	72	6.944	37.5	0.069	0.089	0.021	0.165	0.176	0.164	2	
Haiti	71	47.887	43.662	0.058	0.073	0.032	0.137	0.15	0.134	4	0.094
Nigeria	71	1.408	97.183							0	
South Africa	63	41.27	50.794	0.086	0.112	0.027	0.103	0.126	0.087	14	0.031
Fiji	61	26.23	63.934	0.057	0.074	0.02	0.123	0.137	0.121	6	0.225
Chile	60	13.333	85	0.102	0.127	0.035	0.148	0.183	0.138	9	
Peru	59	0	96.61	0.072	0.094	0.018	0.121	0.134	0.117	2	
Myanmar	58	41.379	44.828	0.203	0.265	0.105	0.493	0.513	0.49	3	0.614
Madagascar	54	22.222	77.778							0	
Portugal	53	50.943	24.528	0.083	0.156	0.034	0.095	0.129	0.077	7	0.168
Panama	53	37.736	35.849	0.104	0.129	0.041	0.288	0.301	0.284	4	0.466
Bahamas	53	64.151	30.189							0	
Trinidad and Tobago	42	50	33.333							0	
Costa Rica	41	51.22	43.902	0.068	0.085	0.026	0.179	0.187	0.178	3	0.098
Guyana	41	4.878	70.732							0	

Venezuela	39	38.462	58.974							0	
El Salvador	35	25.714	65.714	0.102	0.131	0.035	0.271	0.281	0.268	2	
Ukraine	35	54.286	37.143							0	
Dominican Rep.	32	50	40.625							0	
Nicaragua	32	21.875	65.625							0	
Poland	31	77.419	9.677	0.057	0.071	0.031	0.128	0.147	0.122	4	0.171
Jamaica	25	28	64							0	
Montenegro	25	8	28							0	
Norway	22	86.364	4.545	0.074	0.093	0.02	0.131	0.157	0.112	34	0.088
Solomon Is.	21	4.762	85.714							0	
Ghana	20	0	100							0	
Pakistan	18	0	94.444	0.128	0.191	0.038	0.282	0.29	0.28	2	
Cambodia	15	0	73.333							0	
Netherlands	14	64.286	28.571	0.09	0.122	0.041	0.217	0.26	0.196	51	0.401
Mozambique	14	21.429	64.286							0	
Sri Lanka	13	0	100	0.081	0.1	0.027	0.166	0.172	0.164	3	
Papua New Guinea	13	46.154	30.769							0	
Egypt	12	16.667	75	0.09	0.118	0.051	0.344	0.349	0.34	2	0.189
United Arab Emirates	12	0	100							0	
Honduras	11	0	63.636							0	
North Korea	11	18.182	63.636							0	
Finland	10	100	0	0.059	0.075	0.026	0.14	0.162	0.129	12	0.118
Oman	10	0	100	0.116	0.147	0.049	0.234	0.241	0.234	4	
Israel	10	0	60	0.113	0.125	0.064	0.197	0.204	0.184	1	
Albania	10	0	20							0	
Guatemala	10	10	50							0	
Lebanon	10	50	10							0	
Bosnia and Herz.	9	0	0							0	
Suriname	9	0	33.333							0	
Brunei	8	0	100							0	
Lithuania	8	50	50							0	
Iran	7	0	100	0.114	0.173	0.051	0.233	0.238	0.233	2	
Algeria	7	14.286	57.143							0	
Liberia	7	42.857	57.143							0	

Timor-Leste	7	14.286	71.429							0	
Uruguay	7	0	71.429							0	
Bulgaria	6	50	50	0.115	0.144	0.075	0.34	0.346	0.339	5	0.159
Georgia	6	0	50							0	
New Caledonia	6	16.667	83.333							0	
Somalia	6	0	66.667							0	
Yemen	6	0	100							0	
Kenya	5	0	100	0.139	0.167	0.037	0.104	0.122	0.097	2	0.102
Greenland	5	0	80							0	
Senegal	4	25	75	0.079	0.105	0.037	0.215	0.226	0.212	2	0.156
Romania	4	100	0	0.089	0.108	0.063	0.134	0.135	0.134	1	
Tunisia	4	25	75							0	
Estonia	3	100	0	0.067	0.085	0.03	0.156	0.18	0.147	6	0.269
Cameroon	3	0	33.333							0	
Cyprus	3	33.333	66.667							0	
Belize	2	50	0							0	
Gabon	2	50	50							0	
Gambia	2	0	100							0	
Kuwait	2	0	100							0	
Latvia	1	100	0	0.063	0.085	0.031	0.247	0.314	0.24	6	0.108
Belgium	1	100	0	0.096	0.133	0.043	0.107	0.122	0.056	2	
Eq. Guinea	1	0	100							0	
Guinea-Bissau	1	100	0							0	
Qatar	1	0	100							0	
Sierra Leone	1	0	100							0	
Tanzania	1	0	100							0	
COK	0			0.051	0.064	0.019	0.126	0.132	0.125	5	0.075
ASM	0			0.064	0.083	0.031	0.112	0.116	0.111	4	0.086
Dominican Republic	0			0.072	0.09	0.044	0.211	0.221	0.208	4	0.148
KIR	0			0.076	0.095	0.019	0.135	0.146	0.133	4	0.008
MDV	0			0.056	0.07	0.021	0.077	0.088	0.075	4	0.033
MHL	0			0.078	0.1	0.02	0.154	0.168	0.152	3	0.144
TON	0			0.055	0.068	0.018	0.128	0.144	0.124	3	0.34
United Republic of Tanzania	0			0.168	0.23	0.059	0.065	0.08	0.051	3	

Vanuatu	0			0.066	0.081	0.03	0.13	0.139	0.13	3	
CPV	0			0.046	0.058	0.024	0.087	0.095	0.086	2	0.011
CUW	0			0.051	0.063	0.033	0.121	0.124	0.119	2	
Djibouti	0			0.138	0.21	0.076	0.219	0.224	0.218	2	
FSM	0			0.098	0.124	0.025	0.161	0.171	0.16	2	
GRD	0			0.059	0.073	0.031	0.1	0.107	0.1	2	
HKG	0			0.113	0.141	0.047	0.294	0.323	0.286	2	
Iceland	0			0.086	0.126	0.05	0.074	0.093	0.033	2	
MUS	0			0.097	0.121	0.038	0.206	0.213	0.204	2	0.189
Namibia	0			0.062	0.077	0.026	0.104	0.112	0.101	2	
SGP	0			0.09	0.121	0.049	0.218	0.251	0.211	2	
SYC	0			0.097	0.127	0.034	0.205	0.214	0.203	2	
Slovenia	0			0.214	0.27	0.04	0.621	0.641	0.622	2	
Solomon Islands	0			0.095	0.12	0.027	0.133	0.147	0.131	2	
TUV	0			0.066	0.084	0.017	0.123	0.134	0.122	2	0.132
The Bahamas	0			0.073	0.101	0.041	0.314	0.514	0.294	2	
WSM	0			0.059	0.078	0.019	0.153	0.158	0.152	2	
DMA	0			0.043	0.051	0.042				1	
Mauritania	0			0.08	0.124	0.026	0.119	0.128	0.117	1	0.13
PYF	0			0.114	0.153	0.049	0.592	0.616	0.585	1	
VCT	0			0.057	0.074	0.031	0.068	0.076	0.067	1	

[Table S3.2] *ECCC evaluation results per country.*

country	n_events	hit_rate (%)	Miss_rate (%)	mae/q0	rmse/q0	qq/q0	mae/q0.99	rmse/q0.99	qq/q0.99	n_stations	epe_mae
Indonesia	10009	25.917	46.578	0.064	0.091	0.035	0.136	0.154	0.133	20	0.159
United States of America	6574	70.231	18.147	0.073	0.099	0.03	0.173	0.217	0.15	550	0.23
Italy	1739	50.776	34.733	0.041	0.053	0.016	0.081	0.102	0.072	26	0.068
India	1316	20.517	66.261	0.194	0.227	0.088	0.302	0.318	0.301	2	0.271
Malaysia	1288	39.907	38.587	0.077	0.106	0.043	0.118	0.129	0.11	16	0.123
Bangladesh	1090	37.248	45.963	0.236	0.301	0.238	0.625	0.646	0.629	2	
Philippines	912	29.715	45.504	0.068	0.096	0.05	0.173	0.218	0.169	10	0.136
Thailand	671	27.273	60.507	0.06	0.08	0.031	0.1	0.128	0.089	4	
France	569	66.432	17.047	0.062	0.092	0.033	0.098	0.123	0.085	135	0.162

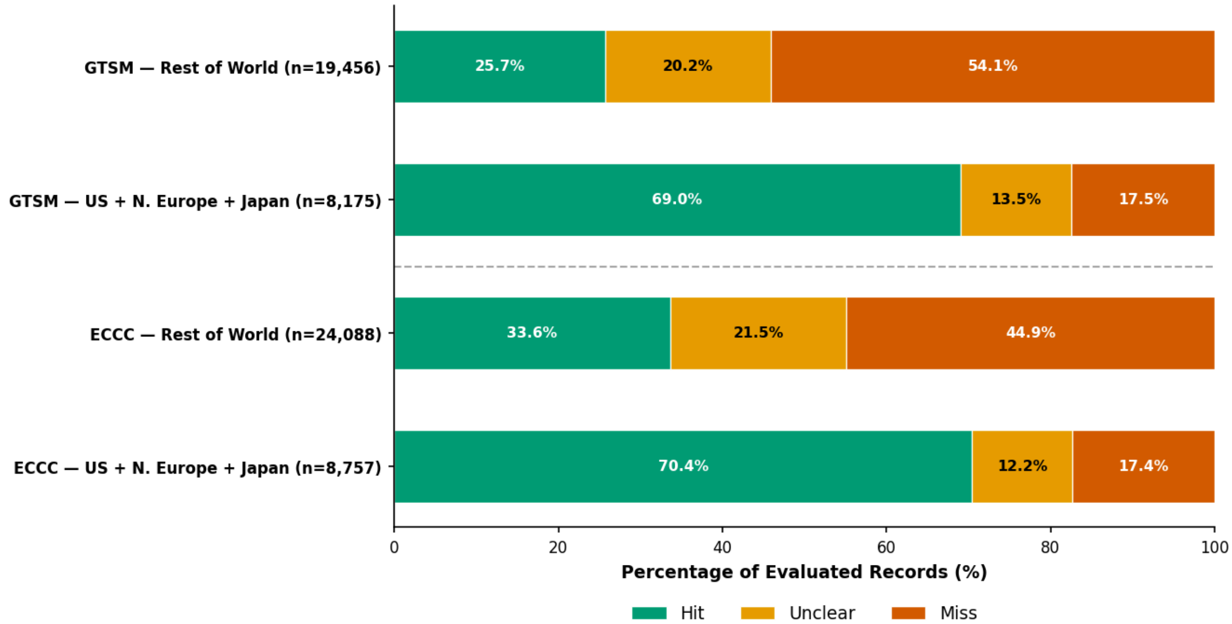
Spain	564	39.539	47.518	0.045	0.068	0.022	0.077	0.095	0.07	63	0.092
Brazil	523	38.05	38.432	0.054	0.075	0.026	0.11	0.126	0.103	6	0.214
United Kingdom	518	59.653	16.023	0.141	0.287	0.083	0.183	0.215	0.166	67	0.198
Mexico	472	33.686	52.331	0.061	0.08	0.031	0.113	0.124	0.109	11	
Taiwan	432	50	36.111	0.095	0.119	0.064	0.11	0.115	0.103	2	
China	359	75.766	13.37	0.065	0.086	0.027	0.136	0.158	0.119	2	0.22
Germany	354	85.311	7.627	0.084	0.117	0.024	0.207	0.26	0.176	72	0.294
Vietnam	352	40.341	44.034	0.073	0.119	0.037	0.12	0.138	0.111	4	0.232
Croatia	334	60.18	28.743	0.05	0.064	0.012	0.105	0.132	0.081	1	
South Korea	334	46.108	35.03							0	
Denmark	298	87.248	6.711	0.068	0.096	0.02	0.242	0.303	0.225	33	0.279
Argentina	255	29.804	37.255	0.092	0.178	0.045	0.141	0.183	0.133	5	0.034
Turkey	249	33.735	39.759	0.065	0.084	0.037	0.194	0.201	0.188	7	0.263
New Zealand	242	44.628	41.736	0.053	0.072	0.022	0.079	0.099	0.067	14	0.087
Canada	235	75.319	10.213	0.08	0.108	0.037	0.135	0.156	0.123	61	0.165
Cuba	225	43.556	30.222							0	
Australia	208	43.269	44.712	0.063	0.086	0.028	0.114	0.143	0.1	94	0.114
Ireland	169	57.396	24.26	0.073	0.112	0.035	0.124	0.147	0.113	14	0.221
Puerto Rico	165	60	37.576	0.034	0.043	0.009	0.065	0.08	0.054	5	0.066
Colombia	143	12.587	57.343	0.041	0.052	0.021	0.098	0.103	0.097	2	0.087
Greece	125	36.8	23.2	0.067	0.087	0.024	0.163	0.184	0.154	6	
Japan	109	57.798	35.78	0.053	0.068	0.018	0.099	0.118	0.089	117	0.116
Russia	104	51.923	33.654	0.085	0.123	0.029	0.172	0.217	0.089	1	0.396
Sweden	100	92	7	0.054	0.069	0.015	0.104	0.128	0.09	34	0.227
Morocco	98	15.306	46.939							0	
Ecuador	87	43.678	24.138	0.039	0.051	0.029	0.051	0.058	0.049	2	
Haiti	80	58.75	26.25	0.043	0.056	0.03	0.091	0.1	0.084	4	0.097
Nigeria	75	1.333	92							0	
Myanmar	70	48.571	40	0.172	0.236	0.119	0.407	0.43	0.394	3	0.522
Peru	66	1.515	93.939	0.033	0.052	0.018	0.052	0.06	0.049	2	
Chile	65	10.769	84.615	0.073	0.093	0.048	0.153	0.181	0.148	9	
Fiji	65	26.154	63.077	0.035	0.049	0.018	0.045	0.059	0.036	6	0.138
South Africa	63	44.444	52.381	0.058	0.082	0.019	0.086	0.106	0.078	14	0.137
Madagascar	62	20.968	69.355							0	
Bahamas	57	61.404	21.053							0	
Poland	55	63.636	14.545	0.045	0.059	0.01	0.095	0.116	0.088	4	0.146

Jamaica	55	43.636	41.818							0	
Portugal	53	60.377	26.415	0.057	0.135	0.029	0.092	0.124	0.083	7	0.166
Panama	53	69.811	15.094	0.071	0.088	0.034	0.087	0.104	0.082	4	0.144
Venezuela	52	28.846	55.769							0	
Costa Rica	45	53.333	42.222	0.045	0.056	0.023	0.072	0.077	0.071	3	0.101
Trinidad and Tobago	44	52.273	36.364							0	
El Salvador	38	10.526	55.263	0.058	0.079	0.035	0.089	0.102	0.086	2	
Guyana	36	8.333	58.333							0	
Ukraine	35	48.571	45.714							0	
Dominican Rep.	34	23.529	32.353							0	
Montenegro	32	25	43.75							0	
Ghana	27	0	81.481							0	
Nicaragua	27	22.222	74.074							0	
Netherlands	25	68	20	0.089	0.129	0.045	0.221	0.265	0.198	71	0.28
Norway	23	91.304	4.348	0.053	0.068	0.015	0.081	0.099	0.06	34	0.074
Pakistan	20	60	35	0.07	0.134	0.035	0.139	0.149	0.138	2	
Sri Lanka	18	5.556	61.111	0.034	0.045	0.014	0.079	0.086	0.078	3	
Cambodia	17	35.294	64.706							0	
Honduras	16	25	62.5							0	
Egypt	15	20	66.667	0.046	0.069	0.031	0.245	0.252	0.241	2	0.103
Solomon Is.	15	26.667	53.333							0	
Albania	14	21.429	57.143							0	
Lithuania	14	28.571	71.429							0	
Mozambique	14	35.714	35.714							0	
Papua New Guinea	14	42.857	35.714							0	
Israel	13	7.692	76.923	0.072	0.079	0.053	0.096	0.1	0.087	1	
United Arab Emirates	12	0	91.667							0	
North Korea	11	18.182	36.364							0	
Suriname	11	0	63.636							0	
Finland	10	100	0	0.047	0.061	0.011	0.084	0.107	0.06	12	0.099
Oman	10	0	100	0.079	0.11	0.045	0.157	0.166	0.154	4	
Brunei	10	10	70							0	
Guatemala	10	50	30							0	
Lebanon	10	50	50							0	

Bosnia and Herz.	9	88.889	0							0	
Uruguay	9	22.222	55.556							0	
Bulgaria	7	28.571	57.143	0.117	0.147	0.062	0.341	0.347	0.341	5	0.182
Iceland	7	0	100	0.052	0.091	0.041	0.053	0.077	0.026	2	
Iran	7	0	100	0.07	0.14	0.037	0.129	0.141	0.129	2	
Algeria	7	42.857	28.571							0	
Liberia	7	0	85.714							0	
Timor-Leste	7	14.286	28.571							0	
Kenya	6	0	83.333	0.05	0.067	0.02	0.097	0.107	0.096	2	0.069
Senegal	6	16.667	50	0.044	0.07	0.024	0.16	0.179	0.157	2	0.139
Georgia	6	33.333	33.333							0	
New Caledonia	6	16.667	83.333							0	
Somalia	6	16.667	66.667							0	
Yemen	6	0	100							0	
Greenland	5	20	60							0	
Romania	4	75	0	0.083	0.101	0.055	0.125	0.127	0.125	1	
Estonia	3	100	0	0.053	0.07	0.013	0.081	0.101	0.062	6	0.045
Cameroon	3	0	33.333							0	
Cyprus	3	33.333	66.667							0	
Tunisia	3	33.333	66.667							0	
Belize	2	50	0							0	
Gabon	2	50	50							0	
Gambia	2	0	100							0	
Kuwait	2	0	100							0	
Latvia	1	100	0	0.059	0.083	0.019	0.183	0.258	0.154	6	0.163
Belgium	1	100	0	0.077	0.107	0.03	0.123	0.14	0.085	2	
Eq. Guinea	1	0	100							0	
Guinea-Bissau	1	0	100							0	
Qatar	1	0	100							0	
Sierra Leone	1	0	0							0	
Tanzania	1	0	100							0	
COK	0			0.036	0.045	0.014	0.068	0.084	0.065	5	0.095
Dominican Republic	0			0.051	0.063	0.027	0.103	0.114	0.101	4	0.083
KIR	0			0.043	0.057	0.023	0.093	0.103	0.089	4	0.006

ASM	0			0.051	0.061	0.027	0.06	0.067	0.053	3	0.11
MHL	0			0.037	0.05	0.018	0.096	0.108	0.094	3	0.065
TON	0			0.041	0.051	0.022	0.09	0.111	0.086	3	0.291
United Republic of Tanzania	0			0.064	0.136	0.029	0.054	0.065	0.039	3	
Vanuatu	0			0.043	0.056	0.026	0.106	0.125	0.105	3	
CPV	0			0.038	0.048	0.017	0.101	0.108	0.098	2	0.043
CUW	0			0.036	0.045	0.013	0.063	0.071	0.062	2	
Djibouti	0			0.073	0.172	0.056	0.134	0.137	0.134	2	
FSM	0			0.05	0.066	0.016	0.08	0.086	0.079	2	
GRD	0			0.04	0.052	0.016	0.057	0.069	0.055	2	
HKG	0			0.074	0.095	0.034	0.195	0.232	0.168	2	
MUS	0			0.068	0.089	0.04	0.2	0.211	0.197	2	0.12
Namibia	0			0.038	0.051	0.02	0.039	0.047	0.034	2	
SGP	0			0.106	0.138	0.079	0.203	0.245	0.19	2	
SYC	0			0.051	0.077	0.028	0.12	0.127	0.119	2	
Slovenia	0			0.224	0.281	0.025	0.577	0.596	0.573	2	
Solomon Islands	0			0.054	0.071	0.025	0.1	0.109	0.099	2	
The Bahamas	0			0.055	0.08	0.025	0.186	0.417	0.146	2	
WSM	0			0.042	0.061	0.023	0.042	0.048	0.035	2	
DMA	0			0.049	0.063	0.046				1	
Mauritania	0			0.049	0.099	0.019	0.083	0.088	0.082	1	0.106
PYF	0			0.097	0.137	0.062	0.59	0.616	0.583	1	
VCT	0			0.045	0.061	0.015	0.093	0.108	0.092	1	

S4. Data-Rich vs. Data-Sparse Regional Breakdown



[Figure S4] *Regional event detection performance, broken down into data-rich (US, Northern Europe, Japan) and data-poor regions.*

S5. Meta-Event Aggregation Analysis

As an attempt to identify "meta-events," i.e., connected records that might belong to the same underlying event, we analyzed 20 different parameter combinations (5 distance × 4 time delta thresholds) to group the 33,293 records.

We used the following criteria:

- Distance is calculated between polygon centroids (km).
- Time delta is calculated as the maximum gap between date ranges (days). 0d = must overlap, 1d = allow 1-day gap, etc.
- Merging: transitive via Union-Find (i.e., if A↔B and B↔C, then all three are in the same meta-event).

[Table S5] *Number of meta-events depending on aggregation thresholds.*

Method	#Meta-Events	#Multi-Event Clusters	Largest Cluster	Mean Size
1km, 0d	28,994	2,197	74	1.15
1km, 1d	28,882	2,233	78	1.15
1km, 2d	27,951	2,930	78	1.19
1km, 7d	26,515	3,716	79	1.26
5km, 0d	20,310	4,758	95	1.64
5km, 1d	20,038	4,775	105	1.66
5km, 2d	19,304	4,997	109	1.72
5km, 7d	18,137	5,119	159	1.84
10km, 0d	15,878	5,224	125	2.10
10km, 1d	15,532	5,212	125	2.14
10km, 2d	14,910	5,269	127	2.23
10km, 7d	13,869	5,138	203	2.40
50km, 0d	9,111	4,259	388	3.65
50km, 1d	8,721	4,176	395	3.82
50km, 2d	8,220	4,090	493	4.05
50km, 7d	7,345	3,793	503	4.53
100km, 0d	7,310	3,702	556	4.55
100km, 1d	6,880	3,573	556	4.84
100km, 2d	6,428	3,453	560	5.18
100km, 7d	5,615	3,160	694	5.93