Groundsource: A Dataset of Flood Events from News

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Abstract

High-quality historical flood data is critical for disaster risk management, infrastructural planning, and climate change attribution, however, existing global archives are constrained by sparse geographical coverage, coarse spatial resolution, or reliance on prolonged satellite observation. To address this gap, we introduce *Groundsource*, an open-access global dataset comprising 2.6 million high-resolution historical flood events, curated from the automated processing of over 5 million news articles across more than 150 countries. Our methodology leverages Gemini large language models (LLMs) to systematically extract structured spatial and temporal data from unstructured journalistic text. Comprehensive technical validation demonstrates that the pipeline achieves an 82% practical precision rate in manual evaluations. Furthermore, spatiotemporal matching against established external databases reveals recall capturing 85% to 100% of severe flood events recorded in the Global Disaster Alert and Coordination System (GDACS) between 2020 and 2026. By transforming unstructured global news media into a structured, localized event archive, *Groundsource* provides a massive-scale, extensible resource to support the training of predictive hydrological models, quantify historical exposure, and advance global disaster research.

1 Background & Summary

Natural disasters pose a continuous threat to global populations and economies[1;2], with floods ranking among the most frequent and destructive of these hazards[3]. Mitigating flood risks and hazards is a core objective of many areas of research, including the training and evaluation of hydrological forecast models[4;5], climate change attribution studies[6–9], future risk projection[10], and disaster risk management[11;12]. Progress across these diverse domains often depends on robust historical baselines; specifically, records of past flood events are needed to validate models and ground theoretical projections in empirical observations. Furthermore, globally consistent flood records inform practical applications, such as guiding urban planning[13], optimizing emergency response[14;15], and accurately quantifying insurance protection gaps[16;17].

Unlike, for example, seismic events, which are systematically recorded and triangulated by standardized global sensor networks[18], hydro-meteorological hazards lack a unified global observation infrastructure, with traditional physical stream gauge networks frequently suffering from geographic sparsity and declining maintenance[19]. An example of this type of database for historical flood events is the United States based Storm Events Database[20], maintained by the US National Centers for Environmental Information. This is a high quality and comprehensive dataset that contains hundreds of thousands of manually collected storm-related events, such as tornadoes, floods, hail, etc., from various sources including emergency management officials, local law enforcement officials, newspaper clipping services and the general public. Similar datasets are not maintained in most countries.

Existing *global* flood events datasets are limited in scope and coverage (Table 1). For example, the Global Disaster Alert and Coordination System (GDACS)[21] contains 10,389 events between 2000 and 2026, focusing mainly on high impact events. The United Nations Office for Disaster Risk Reduction (UNDRR) DesInventar system[22] aggregates local government incident reports, but it is geographically restricted to participating nations and is inconsistently maintained across borders due to varying national reporting standards, data collection methodologies, and resource constraints. Satellite-derived archives, such as the Dartmouth Flood Observatory (DFO)[23] and the Global Flood Database (GFD)[2], provide inundation footprints but are inherently constrained by physical constraints such as satellite overpass frequencies, cloud cover, and bias toward large, prolonged events.

Table 1: Overview of major existing global and regional flood event databases.

Database	Primary Data Sources	Total Events[1] (Approx.)	Citation
NOAA Storm Events	Manual curation, local reports	$>$1.7 Million	20
DesInventar (UNDRR)	National/local government reports	$>$500,000	22
EM-DAT (CRED)	Institutional reports, governments	$>$26,000	24
GDACS	Multi-source monitoring	$\sim$10,000	21
Dartmouth Flood Observatory (DFO)	Satellite imagery, news	$\sim$5,000	23
Global Flood Database (GFD)	Satellite imagery (MODIS)	913	2
Global Flood Monitor (Social Media)	Social media (X/Twitter)	$>$10,000	25
NatCatSERVICE (Munich Re)	Insurance claims, media	$>$30,000	26

[1]Total events, not restricted to floods.

Historical events are abundant in unstructured data sources, such as news articles or governmental reports, and several of the datasets in Table 1 utilize this type of information in various ways. However, unstructured textual data require significant manual effort for extraction and standardization.

Advancements in generative AI allow us to overcome a lot of these constraints. In this paper, we introduce *Groundsource*, an open-access global dataset comprising 2.6 million historical flood events curated from processing over 5 million web-based news articles in more than 150 countries. *Groundsource* provides event-based data at daily temporal resolution and localized spatial boundaries from the year 2000 to the present.

2 Methods

While the current pipeline is optimized for extracting historical flood events to support hydrological studies and flood forecasting, the underlying methodology is, in principle, agnostic to specific hazard types. To achieve a global scale, the ingestion and entity-recognition stages of this pipeline utilize proprietary Google infrastructure (specifically, the WebRef named entity recognition system and the Read Aloud User-agent). However, the complete extraction methodology, Large Language Model (LLM) prompts, and spatiotemporal aggregation logic are documented in full. This transparency ensures that the fundamental pipeline architecture can be adapted by researchers utilizing open-source named entity recognition algorithms and alternative language models.

The construction of the *Groundsource* dataset follows a four-stage automated pipeline:

- **Raw News Article Ingestion:** Publicly available web articles mentioning floods are aggregated using Google's WebRef named entity recognition system. For each identified URL, the core article text and publication date are extracted, and initial geographic location entities are annotated.
- **LLM-Based Extraction (Gemini Analysis):** The raw text is processed using Gemini (version 3 Flash)[27–29] to identify structured data. The model determines whether the article reports a specific, actual flood event and subsequently extracts the precise dates and local geographic entities affected.

- **Geocoding and Spatial Mapping:** The specific location names extracted by the LLM are mapped to standardized spatial polygons using the Google Maps Geocoding API[30].
- **Aggregation and Filtering:** The extracted location-date pairs are aggregated into cohesive spatiotemporal events. Entries reporting the same location on consecutive days are concatenated, and morphological filters are applied to remove implausible geometries and erroneous records.

2.1 Raw News Article Ingestion

The dataset construction begins by aggregating publicly available news articles published since the year 2000 using Google's web crawler. To isolate articles relevant to flood events, we filter the crawled documents using Google's WebRef named entity recognition system. WebRef assigns a topicality score (ranging from 0 to 1) to each webpage, which quantifies how central a specific entity, in this case, "flood", is to the document's overall content. By applying a minimum topicality score threshold of 0.6, we select articles where flooding is a primary subject. This initial filtering process yielded 9.5 million URLs.

A manual review of a random subset of these initial articles indicated that approximately 50% reported on actual historical flood events. The remaining articles referenced flooding in secondary contexts, such as local policy discussions, insurance and aid allocations, or warnings for potential future events. Consequently, while the topicality score effectively isolates flood-related documents, further downstream processing is required to filter out non-event articles.

To extract the relevant text from the filtered URLs, it is necessary to discard extraneous web elements such as navigation menus, advertisements, and HTML formatting. We utilized the internal API of the Google Read Aloud User-agent[31] for this task. This service, originally designed to parse web documents for text-to-speech applications, effectively isolates the primary textual content of an article and extracts its corresponding publication date.

The Read Aloud API currently supports 80 widely spoken languages; articles written in unsupported languages, or those hosted on websites that block automated agents, are discarded. This extraction step narrows the dataset to approximately 7.5 million accessible articles. To standardize the text for downstream processing, all non-English articles are translated into English using the Google Cloud Translation API[32]. Finally, we apply the WebRef system to both the original and translated texts to identify and extract all named entities classified as geographic locations. These extracted location tags are stored alongside the article text to serve as a candidate pool, which the LLM evaluates in the subsequent phase to pinpoint the precise sites of flooding.

2.2 LLM-Based Extraction (Gemini Analysis)

Extracting structured spatiotemporal event data from unstructured journalistic text presents significant NLP challenges. Simple keyword-matching algorithms are insufficient because causal links between mentioned locations, timeframes, and the actual flood event are frequently ambiguous in news reports. Furthermore, flood terminology varies across regions; for example, the words "street flood" might describe a minor infrastructure failure (such as a burst water main) in one country, but significant pluvial flooding in another. Journalistic reporting also exhibits highly variable spatial and temporal granularity. Articles may report flooding across an entire large administrative district without specifying the affected towns, or detail specific inundated intersections without broader geographic context. Temporally, reports often rely on relative references (e.g., "recently" or "for several days") which must be correctly anchored to the article's publication date to determine the precise timing of the event.

To overcome these complexities, we developed a structured prompt for the Gemini LLM. To engineer and formally evaluate this prompt, a ground-truth dataset was constructed by manually annotating 250 randomly selected news articles. Human raters evaluated each article to document four key elements: (1) whether the text reported a specific, verifiable flood event; (2) the precise dates of the flooding; (3) the granular names of affected locations; and (4) the corresponding geographic identifiers within the Google Maps database. This annotated corpus was divided equally such that 125 articles were used for prompt engineering, while the remaining 125 were reserved to evaluate the extraction pipeline's precision and recall.

The engineered prompt guides the LLM through a strict, four-step analytical pipeline to ensure data quality and standardization. The output is a single, structured JSON object containing the extracted variables. The full prompt is reproduced in Appendix A, and the steps encoded into the prompt are summarized as follows:

1. **Classification (Filtering):** The model first evaluates the article to confirm it describes a singular, actual, and ongoing or past flood event. Articles discussing future flood warnings, infrastructural preparations, risk modeling, or multiple disjointed events are immediately rejected to prevent false positives.
2. **Temporal Extraction:** If a valid event is confirmed, the model identifies specific dates on which flooding occurred. The LLM is explicitly instructed to anchor relative temporal references (e.g., "last Tuesday") against the provided article publication date. To prevent logging speculative events, dates extending past the publication date are strictly excluded.
3. **Spatial Extraction:** The model identifies granular geographic locations explicitly described as inundated, submerged, or flooded. To maintain high spatial resolution, broader regional mentions (e.g., entire countries) and locations merely described as "at risk" are ignored.
4. **Location Reconciliation:** Finally, the extracted localized names are matched against the pool of candidate WebRef location entities generated during the ingestion phase. This resolves naming variations (e.g., matching "LDN" to "London") and ties the unstructured text to standardized geographic identification codes.

In total, approximately 5 million of the 7.5 million processed articles were identified by the LLM as reporting an actual flood event. Based on the 125 randomly selected, hand-labeled evaluation articles, this classification step achieved 75% precision and 90% recall. Within this subset of relevant articles, specific event dates were extracted with 61% precision and 74% recall. Finally, when comparing the location identifiers extracted by Gemini against the manual annotations, the spatial extraction achieved 64% precision and 69% recall. It is important to note that returning an imprecise date or location identifier does not necessarily render the extracted event unusable for downstream applications. For instance, if a manual label identifies a specific town, but the LLM returns the identifier for the broader administrative district encompassing that town, the record still provides valid, albeit coarser, spatial evidence of flooding. These reporting nuances and inaccuracies are further evaluated in Section 4.1.

2.3 Geocoding and Spatial Mapping

To assign geographic boundaries to the extracted flood events, we process the location data output by the LLM. Initially, the system verifies whether the LLM successfully linked the flooded location to a specific WebRef entity code during the reconciliation step. When a valid match is present, the corresponding spatial polygons are directly retrieved from the WebRef index. If the LLM could not reconcile the location with a WebRef entity, the raw text string of the flooded location is passed to the Google Maps Geocoding API[30], which converts the location name into a spatial polygon.

Occasionally, the Google Maps database does not contain a defined polygon boundary for a highly specific or localized identifier (such as a minor street intersection or a small village), and instead returns a single point coordinate. In these instances, a small spatial buffer of 0.001° is applied around the returned point to generate a representative, two-dimensional geometry suitable for downstream spatial analysis.

2.4 Aggregation and Filtering

To synthesize the geocoded article data into cohesive flood events, we perform a spatiotemporal aggregation. Because a single significant flood is frequently reported by multiple news outlets over a span of several days, we group the extracted records by their unique geographic location identifiers. Entries reporting the exact same location on the same day, or on consecutive days, are concatenated. This process merges redundant or overlapping daily news reports into a single, continuous event timeline for each specific geographic boundary.

Following aggregation, we apply filters to remove entries that lack a predefined level of spatial or temporal precision. While it may be technically accurate that a flood occurred somewhere within a large nation or along a primary river channel, such broad geometries are uninformative for localized applications. Therefore, we discard any event mapped to a location with a total area exceeding 5,000 km^2 or a maximum diameter greater than 500 km. Additionally, we exclude events with a recorded continuous duration exceeding seven days, as well as any records predating the year 2000. The application of these quality-control filters yields the final *Groundsource* dataset of 2.6 million localized, high-resolution historical flood events.

It is important to note that a single, large-scale real-world flood event may be represented by multiple entries within the *Groundsource* dataset. This occurs when an extensive flood inundates multiple distinct geographic entities (e.g., specific neighborhoods, towns, and districts), all of which are independently annotated by the LLM extraction process. This effect is particularly pronounced in regions with dense, high-resolution media coverage that frequently report flooding at the street level. We explicitly chose to retain this granular, street-level data within the final dataset, as high-resolution spatial boundaries can be valuable for localized hydrological modeling and risk assessment.

3 Data Records

The *Groundsource* dataset is available at https://doi.org/10.5281/zenodo.18647053. To ensure broad compatibility with standard data analysis software and geographic information systems (GIS), the data is provided in a flat tabular format.

The dataset consists of 2,646,302 individual records. Each row represents a distinct spatiotemporal flood observation. Table 2 describes the data that are available for each record in our dataset.

Table 2: Column names and descriptions for each of the spatial, temporal, and identifier data fields recorded for every extracted flood event.

Column Name	Description
uuid	A unique identifier for each record.
area_km2	Area of the reported location polygon.
start_date	The initial day (formatted as YYYY-MM-DD) for which there is documented textual evidence of an ongoing flood.
end_date	The final consecutive day (formatted as YYYY-MM-DD) for which there is documented evidence of the flood. If the aggregated news reports only indicate flooding on a single day, the end date is identical to the start date.
geometry	The spatial boundary of the reported location, utilizing the standard WGS 84 coordinate reference system (EPSG:4326). Depending on the extraction and geocoding process, this geometry may represent a complex polygon (e.g., an administrative district boundary) or a buffered point (e.g., representing a specific street intersection).

As detailed in Section 2.4, users should note that the dataset structure is entity-based rather than meteorology-based. Therefore, a single large-scale meteorological flood may result in multiple separate entries in the dataset. Each of these independently extracted locations is recorded as an independent row with its corresponding geometry and observed dates.

4 Technical Validation

4.1 Manual Precision Validation

To rigorously evaluate the precision of the final *Groundsource* dataset, we conducted a manual review of 400 randomly selected entries. Independent human raters examined the original source news articles corresponding to each extracted event to verify the accuracy of the spatial and temporal data. Each extracted event was evaluated against the ground-truth text and assigned to one of four classification categories:

- **Accurate**: The extracted location polygon and the start and end dates perfectly matched the facts reported in the source article.
- **Approximate**: The extracted data is practically useful for analysis but contains minor discrepancies. Common examples include the LLM extracting a broader administrative district instead of a specific village, or temporal bounds that are offset by a single day due to vague journalistic phrasing (e.g., "over the weekend").

- **Partial**: The flood event genuinely occurred, but the extracted information includes an extra day of reported flooding beyond what could be corroborated by the source text.
- **Wrong**: The extraction is fundamentally incorrect and unusable. This includes false positives (e.g., an article discussing a "flood of emails"), severely miscoded locations (e.g., mapping a city name to the wrong country), or entirely incorrect date ranges.

Based on this manual review, the pipeline achieved a precision of $60\% \pm 5\%$ (95% CI), representing entries where both the extracted location and dates perfectly matched the source text (the "Accurate" category). An additional 22% of the entries were classified as either "Approximate" or "Partial." When combined, this indicates that 82% of the extracted events in the *Groundsource* dataset possess practical utility for downstream geospatial and hydrological analyses. The remaining 18% of evaluated entries were classified as "Wrong" and considered unusable.

An analysis of the erroneous entries revealed several common failure modes within the extraction and geocoding pipeline. Spatial inaccuracies predominantly stemmed from ambiguous geographic nomenclature; for instance, the geocoding API occasionally mapped a commonly used city name to the correct municipality but in the wrong administrative state or country, particularly when the source article lacked sufficient regional context. Temporal errors were frequently caused by the LLM misinterpreting relative date phrasing. Specific examples of these failure modes include:

- **Ambiguous geographic nomenclature**: The location name "Kherbari", for example, refers to multiple distinct localities across different states in India. In such cases, the geocoding service occasionally returned the incorrect spatial polygon from the available options.
- **Publication date discrepancies**: If an article referencing "the past weekend" was updated a week after its initial publication, the pipeline supplied the updated timestamp to the LLM. Consequently, the extracted flood dates were erroneously offset by a week.
- **Temporal hallucination from vague references**: When an article vaguely referenced a flood occurring "last September" without specifying a date, the LLM occasionally imputed an exact, but unverified, start date (e.g., September 1st) rather than rejecting the imprecise temporal bounds.

The actual errors in the dataset are likely not independent and identically distributed (i.i.d.). For instance, the geocoding system may exhibit variable accuracy with location names across different languages, potentially concentrating spatial errors in specific regions or countries. However, stratifying the data to estimate error rates across specific geographic or linguistic slices requires prohibitive manual annotation; therefore, we report only the global precision metric. We invite the scientific community to identify and report systematic errors in *Groundsource*, which will guide improvements in future versions of the dataset.

4.2 Spatiotemporal Distributions and Biases

Temporally, the dataset exhibits a recency bias. Approximately 64% of the recorded flood events occurred between 2020 and 2025, and 15% occurred in 2025 alone. As illustrated in Figure 1, this temporal distribution closely correlates with the volume of flood-related news URLs ingested over time. This trend does not necessarily imply a sudden global increase in the frequency of physical flooding events; rather, it primarily reflects the exponential growth of digitized, publicly accessible news media, the relative scarcity of digitized archival news databases for earlier decades, and the tendency for older online news articles to go offline over time, thereby excluding them from our dataset.

Geographically, event coverage is unevenly distributed across the globe (Figure 2). The spatial density of extracted events correlates directly with regional media coverage density, digital reporting habits, and the 80 languages supported by the Read Aloud API. Consequently, regions where digital news is sparse, or where local news is predominantly published in unsupported languages, are systematically underrepresented in the dataset, reflecting socio-spatial biases in crowdsourced and media-derived geographic data. Users must account for these spatial reporting disparities when conducting cross-regional or global exposure analyses.

As shown in Figure 2, the global spatial distribution of extracted events highlights regions with a high volume of flood reporting (e.g., Europe, South Asia, and Southeast Asia). Furthermore, the map demonstrates that areas with a high density of events in the *Groundsource* dataset align closely with the locations of severe flood events reported in the GDACS database (red points). We explore this alignment with external datasets further in Section 4.3.

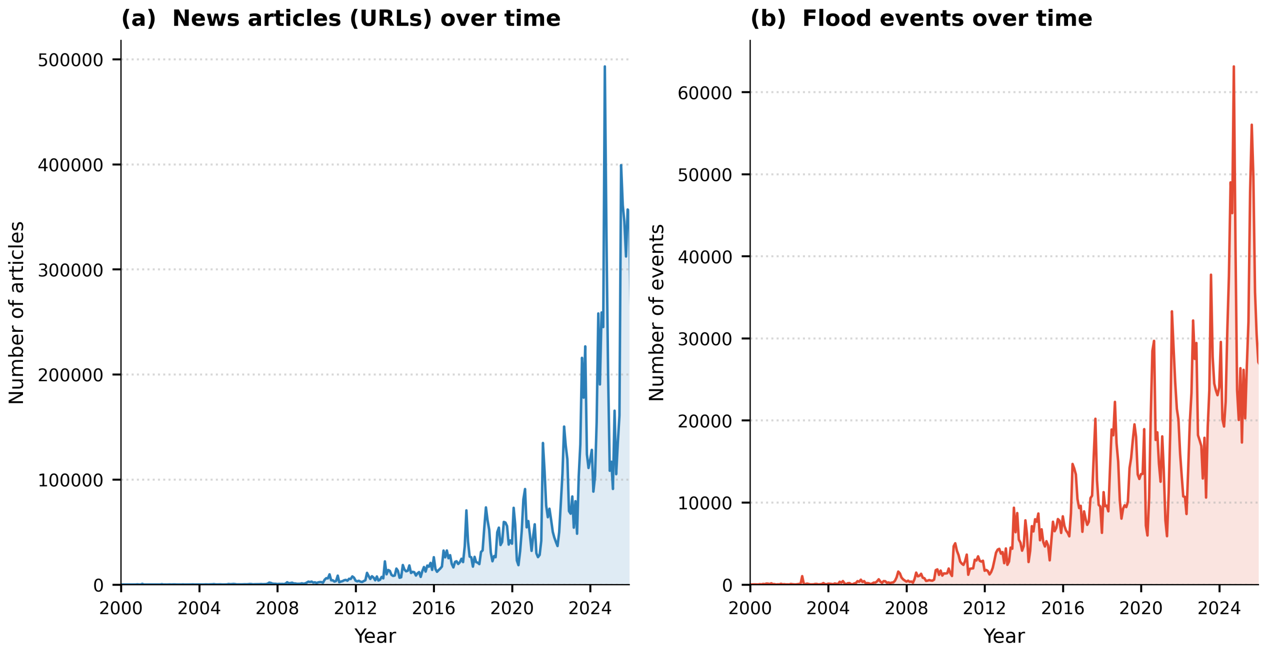

Figure 1: **Temporal distribution of the *Groundsource* dataset.** a) The total number of URLs ingested by the pipeline per month between the years 2000 and 2026. b) The corresponding total number of flood events extracted by the LLM-based pipeline per month over the same period.

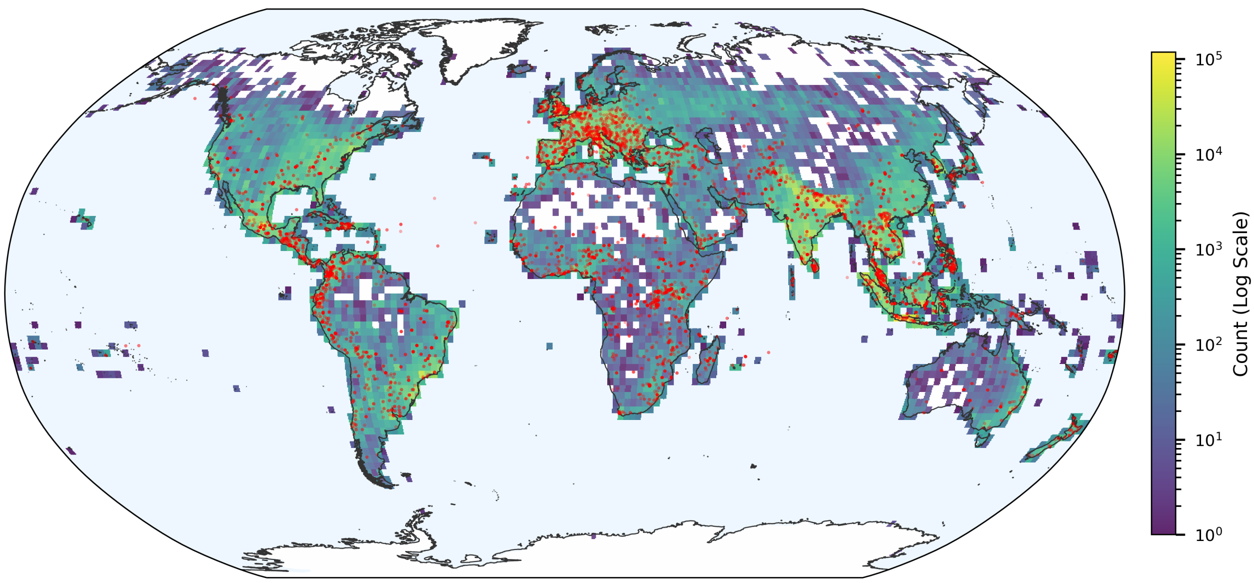

Figure 2: **Global spatial distribution of extracted flood events.** The map displays the total number of flood events extracted by the LLM-based pipeline aggregated per grid cell. The data are visualized using a Robinson projection, with event counts represented by a logarithmic color scale. Red points indicate the spatial centroids of reference flood events from the GDACS database.

Despite these macro-level reporting biases, the dataset provides highly localized spatial boundaries for the events it captures. An analysis of the scale distribution (Figure 3) reveals that the average geographic footprint of an extracted event is 142 km^2. Furthermore, 82% of all recorded events correspond to a spatial footprint of less than 50 km^2. This high proportion of small-scale geometries underscores the dataset's utility for granular, localized hydrological applications. It successfully captures street-level and municipal inundations that are frequently omitted from coarser global hazard databases.

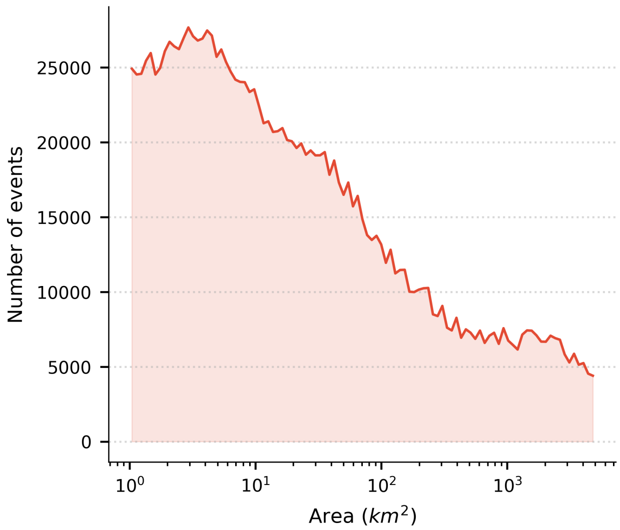

Figure 3: **Distribution of geographic areas for extracted flood events.** The plot displays the total number of *Groundsource* flood events as a function of their spatial footprint, measured in square kilometers. The geographic area on the x-axis is represented on a logarithmic scale

4.3 Recall against External Datasets (GDACS & DFO)

To assess the completeness (recall) of the *Groundsource* dataset, we compared our extracted records against two established global flood databases: the Global Disaster Alert and Coordination System (GDACS) and the Dartmouth Flood Observatory (DFO) archive. Whereas *Groundsource* derives its records from localized news text, GDACS and DFO rely on multi-source humanitarian monitoring and satellite imagery. GDACS is a cooperation framework under the United Nations and the European Commission that provides near real-time alerts for natural disasters, focusing on humanitarian impact. Our analysis considers 6,537 GDACS flood events recorded between 2017 and 2026. The DFO maintains an active archive of large flood events derived primarily from satellite remote sensing and news reports. We compared *Groundsource* against 3,875 DFO events occurring between 2000 and 2023, which is the year of the most recent event in the DFO dataset.

To conduct a standardized comparison across these differing formats, we established a strict set of criteria to define a valid match. A reference event from GDACS or DFO was considered successfully captured (recalled) by *Groundsource* if at least one extracted news event met two conditions simultaneously: (1) **Spatial intersection**: The polygon geometry of the *Groundsource* event must spatially intersect the geographic boundary or buffered centroid of the reference event; and (2) **Temporal overlap**: The recorded start and end dates of the *Groundsource* event must overlap with the active temporal duration of the reference event.

4.3.1 Temporal Recall

Applying this spatiotemporal matching framework, we first analyze the recall performance over time for both datasets, as presented in Table 3. For GDACS, recall is consistently high, achieving 85%–100% for every year from 2020 to 2025 of all GDACS-recorded floods (Figure 4a).

The comparison against the DFO archive, which captures a broader spectrum of flood magnitudes derived from satellite imagery, illustrates the dataset's reliance on modern media ecosystems. While recall against DFO events is relatively lower prior to 2015, the metric exhibits a clear, positive trend over time. This increasing trajectory tracks the historical growth of digitized news articles identified in Section 4.2.

Table 3: **Annual recall of *Groundsource* events against baseline databases.** The table presents the total number of reference events (Total), the number of events successfully matched by the Groundsource pipeline (Match), and the corresponding recall percentage (Rec) evaluated against the Global Disaster Alert and Coordination System (GDACS) and the Dartmouth Flood Observatory (DFO) datasets between the years 2000 and 2026. Dashes indicate periods where the respective database contains no records.

	GDACS			**DFO**		
Year	Total	Match	Rec (%)	Total	Match	Rec (%)
2000	–	–	–	102	14	13.7
2001	–	–	–	164	21	12.8
2002	–	–	–	226	21	9.3
2003	–	–	–	297	30	10.1
2004	–	–	–	194	64	33.0
2005	–	–	–	171	89	52.0
2006	–	–	–	232	90	38.8
2007	–	–	–	241	149	61.8
2008	–	–	–	180	118	65.6
2009	–	–	–	156	87	55.8
2010	–	–	–	175	120	68.6
2011	–	–	–	124	83	66.9
2012	–	–	–	124	91	73.4
2013	–	–	–	102	81	79.4
2014	–	–	–	102	89	87.3
2015	–	–	–	102	95	93.1
2016	–	–	–	113	97	85.8
2017	202	182	90.1	123	115	93.5
2018	121	114	94.2	159	149	93.7
2019	369	320	86.7	141	132	93.6
2020	476	389	81.7	153	139	90.8
2021	813	656	80.7	163	136	83.4
2022	966	779	80.6	175	111	63.4
2023	1082	851	78.7	156	87	55.8
2024	1216	1041	85.6	–	–	–
2025	1231	1043	84.7	–	–	–
2026	61	47	77.0	–	–	–

4.3.2 Spatial Recall

Geographically, the recall of the *Groundsource* dataset exhibits regional variations that closely align with global disparities in media infrastructure. The pipeline demonstrates exceptionally high spatial recall in densely populated, flood-prone regions with robust digital news ecosystems, such as Western Europe, the Philippines, and Bangladesh (Figure 4).

For example, in the United States, the dataset matches 96% ($n = 236$) of GDACS events and 91% ($n = 104$) of DFO events. Similarly in the Philippines (GDACS: $n = 164$; DFO: $n = 35$) and Malaysia (GDACS: $n = 126$; DFO: $n = 19$, recall ranges from 79% to 89%). Conversely, recall drops in regions with limited digital media penetration or where local news is predominantly published in languages not currently supported by the extraction pipeline. For instance, recall drops to 39% ($n = 36$) for GDACS in Papua New Guinea and 50% ($n = 8$) for GDACS in Gabon.

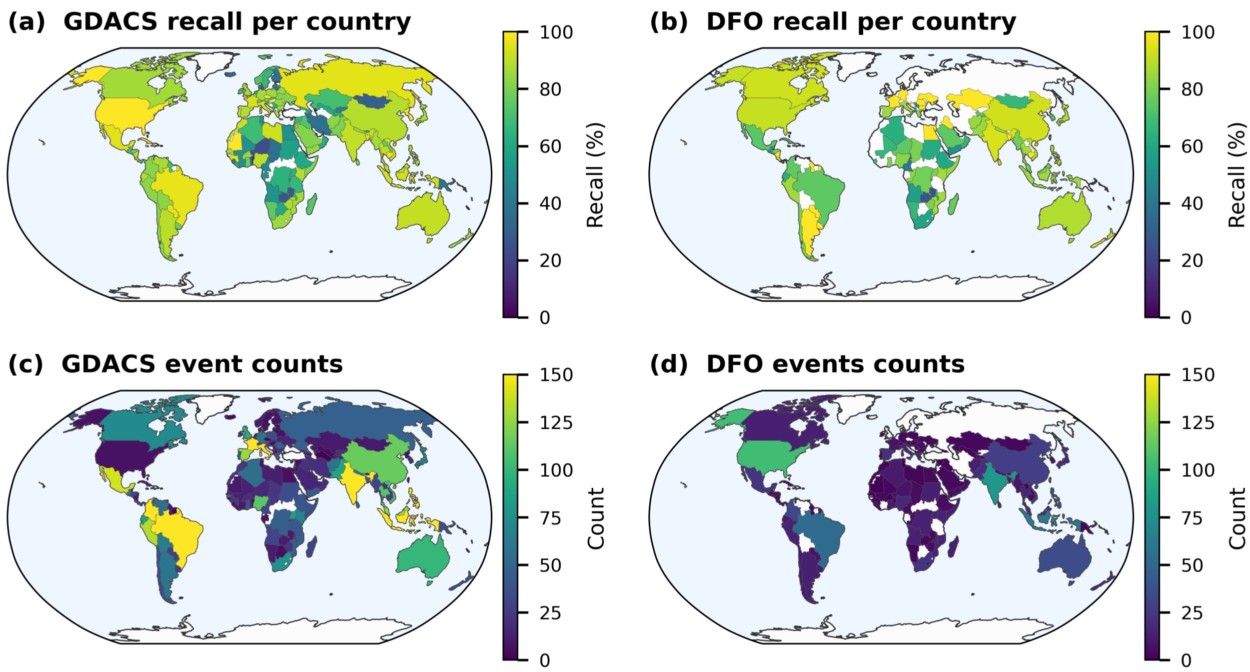

Figure 4: **Global distribution of *Groundsource* recall rates and reference event counts.** Top row: The percentage of successfully matched reference events (recall) per country for the GDACS (a) and DFO (b) databases. Bottom row: The total number of recorded reference flood events per country in the GDACS (c) and DFO (d) databases used for the spatial evaluation.

4.3.3 Severity Correlation

We evaluated the relationship between the severity of a flood and its corresponding recall in comparison to the external datasets. Since our dataset is derived from news media, we hypothesize that events with greater humanitarian or physical impact are more likely to be reported and thus extracted. The data supports this hypothesis for both external sources.

Recall shows a positive and monotonic correlation with the *Alert Level* field in the GDACS dataset (Figure 5a). Recall for green alerts (events manageable by national authorities) is 82% ($n = 6,038$), whereas for major orange ($n = 438$) and red ($n = 61$), recall rises to 99%.

A similar pattern is observed when correlating recall with the *Flood Impact Index* field of the DFO dataset (Figure 5b), which is a metric derived from flood magnitude and duration. Recall is lower for minor events (Index 2 and 3), ranging between 43–65%. However, for high-impact events (Index > 6), recall consistently exceeds 90% (sample sizes shown in figure).

Code availability

No custom code is provided with this manuscript. The data ingestion and extraction pipeline relies on proprietary internal infrastructure; however, the complete extraction methodology and all LLM prompts required to replicate this approach using open-source alternatives are fully detailed in the Methods section and Appendix A.

Author contributions

DC conceived the initial idea for the project. RM and OZ conducted the initial implementation and early research on this project. RM, OZ, FK, AS, IZ, and YN all contributed to the codebase. MB and OZ worked on the prompt engineering. RM, OZ, MB, SF, OG, AH, FK, GL, YM, YN, GN, RS, AS, IZ, and DC contributed to the drafting and critical revision of the manuscript, and all authors approved the final submitted version.

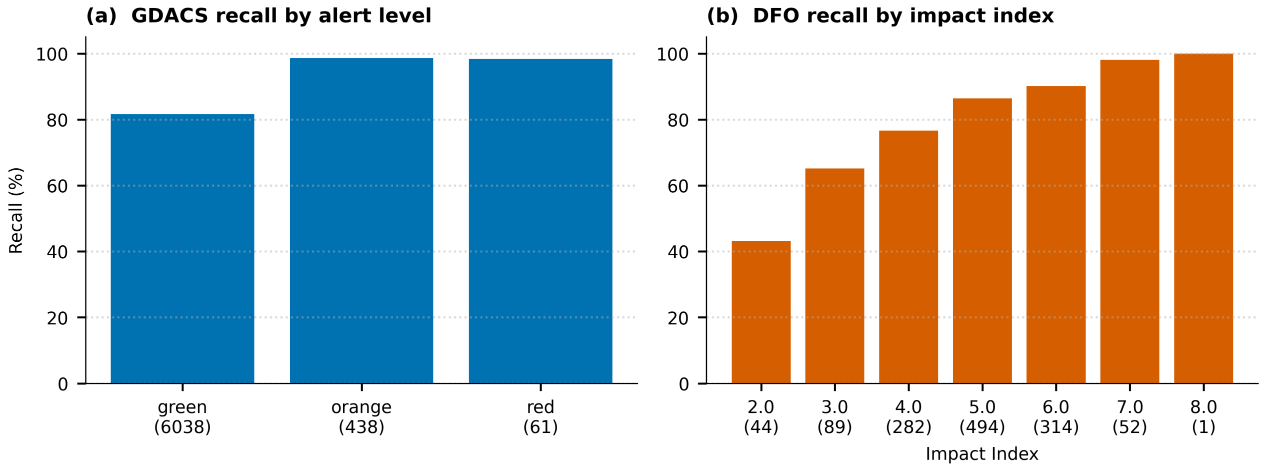

Figure 5: **Evaluation of dataset recall as a function of reported event severity.** a) Recall percentage of the *Groundsource* dataset against GDACS reference events, stratified by GDACS alert levels (green, orange, red). b) Recall percentage against DFO reference events, stratified by the calculated DFO Flood Impact Index. The total number of reference events within each severity category is indicated in parentheses below the respective bars.

Competing interests

The authors declare no competing interests.

Appendix A: Gemini Prompt for LLM-Based Event Extraction

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You are a meticulous flood event analyst. Your task is to analyze the provided article text (text),
     URL (url), and publication date (date) to extract information about a single, specific flood
     event and map locations to a reference database. You must only respond with a single, clean
     JSON object. Do not include any markdown formatting, text, or explanations outside the JSON.

Step-by-Step Instructions:
Phase 1: Flood Event Extraction & Verification
Analyze the article text (en_text), URL (url), and publication date (date) to determine if a single
     flood event occurred and extract verifiable details.

Step 1 - Initial Analysis:
Carefully read the article text, taking note of the publication date.

Step 2 - Core Task - Classify Article Type (The "Gate"):
You must first determine if the article describes a single, actual, ongoing, or past flood event.
     An actual flood is an event that the text describes as a fact that has happened or is currently
     happening.

Crucial Distinction: An article is NOT about an actual flood if it only discusses:

- Warnings/Predictions: Flood warnings, advisories, forecasts, or statements about potential or
     future risk (e.g., "floods may occur," "government warns of floods," "14 states are at risk,"
     "heavy rainfall could cause flooding").

- Policies/Preparations: Flood-related policies, defense projects, community preparations, or
     government meetings.

- Multiple Flood Events: The article describes separate flood events in different locations (e.g.,
     a flood in Brazil and a flood in Italy).

- Other: future risk modeling, or general discussions.

Your Decision:

- If the article describes a single, actual flood event, proceed to Step 3.

- If the article does NOT describe a single, actual flood (i.e., it is any of the types listed
     above), STOP here. Do not proceed. Your final output must be the "No Flood Event" JSON
     structure.

Step 3 - Extract Flood Dates (flood_dates):

Important: Only if you identified a single, actual flood in Step 2

- Identify all specific dates on which the text states flooding definitely occurred for the single
     flood event.

- This can be an explicit date (e.g., "August 26, 2025") or a relative date that can be precisely
     calculated from the publication date (e.g., "yesterday," "last Tuesday").

Exclude:

- Vague dates which cannot be pinpointed (e.g., "last month", "last week", "recently").

- Dates of future predictions or warning periods (e.g., if the article says "flooding is expected
     from Sept 4-8", you must NOT extract these dates).

- Dates of policy meetings or article publication dates (unless the text explicitly states flooding
     occurred on that date).

Format each date as a "YYYY-MM-DD" string.

Constraint: The extracted dates should not be later than the publication date.

The final list should be sorted in ascending order with no duplicates. If no specific dates can be
     determined, this is an empty list ([]).

Step 4 - Extract Flooded Locations (flooded_locations):

Important: Only if you identified a single, actual flood event in Step 2
```

```
Identify all specific locations that the text explicitly states have been flooded, submerged, or
     under water due to the single flood event. Locations must be explicitly described as flooded,
     submerged, or under water, not just experiencing heavy rain. Only include granular locations
     such as cities, neighborhoods, and streets. Do not include vague locations like "Northern half
     of state" or anything bigger than district.

When mentioning a district, write it like - "Haifa district, Israel" and not "Haifa, Israel"

**Exclude:**
* **Future/Warning:** Locations listed as "at risk," "under warning," "may face floods," "could be
     affected," or "preparing for" a flood.
* **Historical/Contextual:** Locations mentioned only as background context or prior events (e.g.,
     "This follows flooding in [Location X] last month," or "[Location Y] had **already**
     experienced flooding by this period"). **Only extract locations that are part of the specific,
     current flood incident described in the article's active timeline.**
* **Very big locations:** Locations that are state or bigger (e.g., "This flood also affected this
     country" we don't want to mark this place as flooded because it too vogue)

- Format each location to be as detailed and easily searchable as possible (e.g., "Boulder,
     Colorado, USA").

- Prioritize the most specific locations (e.g., street names, neighborhoods, towns over cities,
     cities over regions, regions over countries) and ensure each location is easy to find in a
     simple Google search.

- If a specific location lacks context (e.g., "Main Street" without a city), add the broader
     context (e.g., "Main Street, Anytown").

- If no specific locations are mentioned as actually flooded, submerged, or under water, this is an
     empty list ([]).

Step 5 - Determine Verifiability (is_verifiable_flood):

- This is a boolean (true or false) field.

- Set it to true if, and only if, you were able to extract both at least one specific flood date
     (in Step 3) and at least one specific flooded location (in Step 4).

- In all other cases, set it to false. (This will be false by default if you stopped at Step 2).

Phase 2: Location Reconciliation (Matching)
Take the flooded_locations list from Phase 1 and match each entry against the provided
     all_mids_from_webref reference list.

all_mids_from_webref: A list of potential matches containing a name and a code.

Match Criteria: A match occurs when a location corresponds to an item in all_mids_from_webref at
     the same level of specificity.

Allowed: Variations in spelling or abbreviation (e.g., "LDN" matches "London").

Prohibited: Mismatched scope (e.g., "Soho" [neighborhood] does NOT match "London" [city]).

Instruction
Iterate through each location from Phase 1.

Compare it against every item in all_mids_from_webref.

If a good match is found (same place, same specificity), record the code.

If no match is found, record null and explain why.

Phase 3 - Construct the Final JSON Output:

- Combine all the extracted information into a single JSON object.

- Ensure your entire response is only this JSON object and nothing else.

Inputs
Url:
{url}
```

```
Extracted Publication Date:
{date}

Text:
{text}

all_mids_from_webref:
{all_mids_from_webref}

Output Format
JSON

{{
  "flood_dates": ["YYYY-MM-DD", ...],
  "is_verifiable_flood": true/false,
  "flooded_locations": ["Location 1", "Location 2"],
  "location_matches": [
    {{
      "location": "Location 1",
      "all_mids_from_webref_match": "code_from_reference_list"
    }},
    {{
      "location": "Location 2",
      "all_mids_from_webref_match": null
    }}
  ]
}}

If no actual flood is found in Phase 1:

JSON

{{
  "flood_dates": [],
  "is_verifiable_flood": false,
  "flooded_locations": [],
  "location_matches": []
}}

Take a deep breath. Read the instructions and the inputs again. Each instruction is crucial and
     must be executed with utmost care to produce a perfectly formatted JSON output.
```

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