

Global Disaster Risk Assessment from Emergency Events Database (2013-2023)

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Abstract. This paper defines an Accumulated Risk Index (ARI) to quantify regional risk levels in a global perspective utilizing Emergency Events Database (EM-DAT) from 2013 to 2023. Building on the World Risk Index (WRI) released from World Risk Report 2023, the ARI focuses more on major events caused by multiple natural hazards within 5°×5° latitude-longitude grids, and calculates their accumulative effects during the period. ARI results are presented in two forms including normalized global maps and index rankings of each grid to identify high-risk areas that warrant increased attention. To provide a data foundation for subsequent research at smaller scales, this paper integrates and supplements existing remote sensing images within high-risk areas, publishing them as an open-source 3H Dataset partitioned by grids after standardizing their formats. The unified imagery establishes a valuable resource for deeper insights and more precise analyses in future disaster risk research of developing countries.

1 Introduction

1.1 Background

In association with the compounding effects of climate change and human activities, natural hazards demonstrate a more frequent and intense trend in recent years (Yarveysi et al., 2023; Chamberlain et al., 2024; Wang et al., 2017; Hussain et al., 2023; Taghizadeh-Hesary et al., 2021; Wen et al., 2023; Chitondo et al., 2024; Coronese et al., 2019). Moreover, natural hazards are not isolated, but exhibit clustering features in both time and space dimensions, which indirectly reflect accumulative socio-economic impacts (Ridder et al., 2020; Hufschmidt et al., 2005). It is regrettable that the impacts are also closely correlated with both the frequency and intensity of disaster events. Particularly in developing countries, major events triggered by multiple natural hazards interact with socio-economic vulnerability, resulting in severe human casualties, substantial economic losses, and heightened social unrest (Koks et al., 2019; Rentschler et al., 2022; Baranowski et al., 2020). Consequently, the escalating risk of major disaster events poses a severe challenge to global sustainable development, which underscores the necessity for comprehensive risk assessments.

There is a rapidly increasing recognition on the need for disaster risk assessments, accompanied by growing dialogue (Koks et al., 2019; Ward et al., 2020). In recent years, a large volume of research has been dedicated to assessing the risks of individual hazard or single region (Ridder et al., 2020; Koks et al., 2019; Julià and Ferreira, 2021). However, owing to the inherent complexity and methodological challenges involved, assessing the probable impacts of multiple natural hazards on a global scale has yet to be widely adopted in mainstream practices (Ward et al., 2020; Julià and Ferreira, 2021; Gallina et al., 2016), with only initiatives promoted by renowned organizations such as the United Nations Development Programme (UNDP) being exceptions.

As summarized in Table 1, representative global multi-disaster risk assessments are compiled, with the following aspects of emphasis that warrant further consideration and analysis: 1) Data timeliness: Only a few indices (WRI, CRI, and INFORM) incorporate statistics from the past decade, and some have recently discontinued updates (e.g., CRI). 2) Assessment unit: Most indices adopt national boundaries, which facilitate reliable socio-economic indicator integration but are too coarse to represent the actual geographic scope of natural hazards or support remote sensing-based applications (Shi and Kaspersen, 2015; Dilley, 2005; Paprotny et al., 2018; Mucke et al., 2011). 3) Disaster type: Several indices cover a limited range of natural hazards. For instance, DRI only considers four types with high mortality rates (UNDP, 2004),

40 CRI focuses exclusively on climate disasters (Eckstein et al., 2021), whereas INFORM mixes natural and human-induced hazards (Marin-Ferrer et al., 2017). 4) Assessment indicator: Indicator choices vary widely across indices and often rely on subjective selection (Yarveysi et al., 2023; Dilley, 2005; UNDP, 2004; Marin et al., 2021): from DRI, which only considers death risk as a single dimension (UNDP, 2004), to WRI, which comprehensively evaluates social and economic aspects using 100 different indicators (Frege et al., 2023; Mucke et al., 2022).

45 In the implementation of disaster risk assessments, remote sensing technology is widely regarded as a critical source of spatial information and distribution data (Pittore et al., 2017; Tronin, 2009; Geiß and Taubenböck, 2012). Disaster risk assessment relies heavily on the statistical pertaining to exposure and vulnerability. However, data availability and acquisition costs significantly limit the broader application of remote sensing technology in disaster risk research (Geiß and Taubenböck, 2012; Elliott et al., 2016; Rathje and Adams, 2008; Manfré et al., 2012), especially for developing

50 countries (Herold and Sawada, 2012). Furthermore, there is an inherent trade-off between spatial resolution and coverage area in remote sensing data: higher spatial resolution typically entails a smaller coverage area (Pittore et al., 2017; Geiß and Taubenböck, 2012; Rathje and Adams, 2008). This constraint restricts the practical application of remote sensing technology in regions with limited financial resources or limited access to high-resolution imagery, making thorough disaster risk assessments more difficult.

55 **1.2 Motivation and Objectives**

Despite the substantial progress represented by existing risk indices, two key limitations hinder the identification of recent and spatially concentrated disaster impacts. First, long-term averages of hazard occurrence and socio-economic indicators may obscure the accumulative impacts of recurrent disaster events observed in the most recent decade. However, hazard clusters within short periods can cause compounding disruptions that overwhelm local coping capacities, especially in

60 developing countries (Ridder et al., 2020; Rentschler et al., 2022; Frege et al., 2023). Capturing these near-term accumulative effects therefore requires an index that explicitly emphasizes recent, high-impact disaster events rather than multi-decade averages.

Second, the prevalent use of country-level assessment units restricts the ability to identify sub-national or transboundary hazard clusters. Natural hazards follow geophysical processes rather than political borders, and their spatial footprint often

65 spans multiple administrative units. These concerns were also highlighted in previous research (Paprotny et al., 2018; Mucke et al., 2011) and reinforce the need for methodological innovation.

Motivated by these gaps, this study introduces a global multi-disaster risk assessment index that focuses specifically on the accumulative effects of major disaster events from 2013 to 2023. The index uses $5^{\circ} \times 5^{\circ}$ latitude-longitude grids as its basic assessment unit and incorporates WRI as a contextual weight coefficient. The proposed ARI aims to provide a

70 complementary perspective that links recent disaster dynamics with the underlying socio-economic environment.

The intended purpose of ARI is threefold: 1) For policymakers, ARI helps identify areas where repeated disaster shocks have eroded resilience and thus require priority in preparedness planning and capacity-building initiatives. 2) For practitioners and humanitarian organizations, ARI provides a spatially explicit indicator of recent accumulative disaster activity that can guide early recovery efforts and international assistance coordination. 3) For researchers, ARI offers a

75 complementary lens to existing long-term indices, enabling comparative analyses of short-term disaster accumulation and supporting studies on emerging hazard patterns under climate change.

In addition, in order to facilitate further remote sensing-based research, this study systematically integrates and supplements existing sub-meter visible spectrum remote sensing imagery for ARI-identified high-risk grids, and publishes them as an open-source dataset after standardization. This dataset provides essential support for future studies at finer

80 spatial scales.

Table 1: Representative results of global multi-disaster risk assessment (Shi and Kasperson, 2015; Dilley, 2005; UNDP, 2004; Eckstein et al., 2021; Marin-Ferrer et al., 2017; Frege et al., 2023).

Name	Source	Publication time	Statistic year	Assessment unit	Natural hazard type	Unified parameter	Focus on	Result type
Disaster Risk Index (DRI)	UNDP	2004	1980 ~ 2000	Country	Earthquake, tropical cyclone, flood, drought	Expected death	Mortality	Score
World Risk Index (WRI)	Bündnis Entwicklung Hilft & IFHV	Annual	_*a	Country	Earthquake, tsunami, cyclone, coastal flood, riverine flood, drought, sea-level rise	Exposed people	Population & Social capability	Score & Rank
Global Climate Risk Index (CRI)	Germanwatch	Annual (as of 2021)	2000 ~ 2019	Country	Storm, flood, temperature extreme, mass movement (heat and cold wave etc.)	Death & Economic loss	Population & Economy	Score & Rank
INFORM Risk Index	European Commission	Biannual	_*b	Country	Earthquake, tsunami, coastal flood, riverine flood, tropical cyclone, drought	Exposed people	Population & Social capability	Score
Natural Disaster Hotspots	World Bank & Columbia University (The Hotspots Project)	2005	1981 ~ 2000	2.5' grid	Earthquake, landslide, cyclone, flood, drought, volcano	Death & Economic loss	Population & Economy	Decile
Total Risk Index (TRI)	Beijing Normal University (World Atlas of Natural Disaster Risk)	2015	1951 ~ 2013 & 1949 ~ 2009*c	Country &	Earthquake, landslide, tropical cyclone, flood, drought, volcano, wildfire, storm surge, sand-dust storm, heat wave, cold wave	Death & Economic loss (historical)	Population & Economy	Quintile & Decile
Multi-hazard Risk Index (MhRI)				Country & 0.5° grid & Comparable-geographic unit		Death & Economic loss (expected)		

*a: WRI is calculated based on the latest available data, and its statistic years depends on the update of data sources (Frege et al., 2023);

*b: INFORM uses different sources of statistic data for different natural hazards, and the statistic years are not the same (Marin-Ferrer et al., 2017);

*c: Both TRI and MhRI use EM-DAT data from 1951 to 2013 and China Catastrophe Statistics data from 1949 to 2009 (Shi and Kasperson, 2015; Delforge et al., 2025).

2 Data and Methods

2.1 Disaster event dataset and filtering strategy

The Emergency Events Database (EM-DAT) serves as the primary source of disaster records for this study. A joint initiative of the Centre for Research on the Epidemiology of Disasters (CRED) and the World Health Organization (WHO), EM-DAT was established in 1988 and has since been managed by the University of Leuven (UNDP, 2004; Delforge et al., 2025). The database documents over 26,000 significant events worldwide from 1900 to the present (Delforge et al., 2025), and its combination of open access format and authoritative sources has made it a cornerstone resource in disaster risk research (Wen et al., 2023; Mokhtari et al., 2023; Peduzzi et al., 2012; Formetta and Feyen, 2019).

Considering the timeliness of disaster statistics and reliability of historical records, this study focuses on disaster events for the period 2013-2023 as a preliminary research object. Since EM-DAT typically verifies data from a given year at beginning of the following year (Delforge et al., 2025), the reliability of 2024 data has not been confirmed and is therefore excluded. In addition, earlier EM-DAT records (particularly pre-2000) are known to suffer from reporting inconsistencies and missing entries, especially in developing countries. Therefore, restricting the temporal scope to the past decade ensures higher data completeness and comparability, consistent with the objective of capturing recent accumulative disaster impacts.

This study prioritizes disaster categories associated with structural damage, as building destruction accounts for the majority of casualties and losses in natural hazards (Ceferino et al., 2018a; Ceferino et al., 2018b; Ceferino et al., 2024). EM-DAT's focus on significant events, those likely to trigger humanitarian crises and attract international attention, enhances the reliability of these records (Delforge et al., 2025; Mokhtari et al., 2023; Peduzzi et al., 2012; Formetta and Feyen, 2019).

Table 2: Categories of disasters and number of recorded events.

Disaster subgroup	Disaster type	Disaster subtype	Target disaster events	Major disaster events
Geophysical	Earthquake	Ground movement	284	33
		Tsunami	4	1
Meteorological	Storm	Blizzard/Winter storm	98	7
		Derecho	6	0
		Extra-tropical storm	80	0
		Storm (General)	85	6
		Storm surge	8	0
		Tornado	56	3
		Tropical cyclone	605	62
Hydrological	Flood	Coastal flood	3	0
		Flash flood	346	38
		Flood (General)	1076	114
		Riverine flood	395	48
	Mass movement	Landslide	152	27
		Mudslide	19	5
Total			3217	344

Using a threshold of 50 fatalities (Total Deaths), this study identifies 344 major disaster events for detailed statistical analysis. The selection of “Total Deaths” as the primary criterion reflects its superior reliability and objectivity compared to other metrics. Population-based indicators in EM-DAT, such as “No. Affected” and “No. Homeless”, are less reliable

110 due to varying definitions and estimation methods, which often depend heavily on other metrics or overall event
assessments (UNDP, 2004; Newman and Noy, 2023; Peduzzi et al., 2009). Similarly, economic indicators like “Total
Damage” introduce significant statistical bias due to varying socio-economic capacities across countries with different
development levels (UNDP, 2004; Peduzzi et al., 2009). The ≥ 50 fatalities threshold further excludes small-scale events
that may be more prone to under-reporting, thereby improving representativeness for global-scale analysis.

115 Table 2 presents the selected disaster categories and their corresponding event counts, following EM-DAT’s classification
system of subgroups, types, and subtypes. A notable aspect of this classification involves “Mass movement” and its
subtype “Landslide”, which are categorized as either dry or wet events under the “Geophysical” and “Hydrological”
subgroups, respectively (Delforge et al., 2025). For statistical clarity, dry landslides, representing only 1.3% of cases, are
consolidated within the “Hydrological” subgroup.

120 This study primarily focuses on four types of natural hazards: earthquakes, storms, floods, and mass movements,
encompassing three disaster subgroups and fifteen disaster subtypes. Notably, four subtypes (derecho, extra-tropical storm,
storm surge, and coastal flood) are excluded from final analysis, as there are no records of major events with at least 50
fatalities during the period.

2.2 Spatial standardization

125 A significant challenge in analyzing EM-DAT data arises from its non-standardized recording of disaster locations
(Lindersson et al., 2020; Rosvold and Buhaug, 2021; Nohrstedt et al., 2022). While precise latitude-longitude coordinates
are available for all earthquake events and select other disasters, the majority of events are documented only through
textual descriptions of affected locations, such as city and village names. The variable nature of disaster centers and
affected areas, often spanning extensive geographical regions, further complicates spatial analysis of these events.

130 This study addresses the standardization challenge through a systematic approach to location data processing. For each
event, a single representative location is selected from the available textual descriptions, prioritizing sites that both lie near
the affected area’s center and demonstrate significant damage. The latitude-longitude coordinates for these selected
locations are derived from administrative boundary data, providing an approximate but consistent method for disaster
center identification. For events spanning multiple administrative units, one representative coordinate is selected to avoid
135 double-counting across neighbouring grid cells. This approach maintains consistency across the global dataset while
acknowledging inherent spatial uncertainty, which is further discussed in Section 5, and forms the basis for the grid-based
aggregation used in the ARI. To enhance transparency and reproducibility, several representative examples of this
conversion are provided in Table 3, which documents the original location descriptions, selected representative sites, and
corresponding coordinates.

140 **Table 3: Example of translating textual descriptions of event locations into latitude-longitude coordinates.**

Event date	Disaster type	Disaster subtype	Country	Location (textual description & geographic center)	Latitude (°)	Longitude (°)
2021-8	Earthquake	Ground movement	Haiti	Nippes Department (18.40°N, 73.00°W)	18.41*	-73.48*
				Grand’Anse Department (18.55°N, 74.00°W)		
				Sud Department (18.35°N, 73.55°W)		
2019-9	Storm	Tropical cyclone	Bahamas	Great Abaco Island (26.39°N, 77.09°W)	26.47	-77.18
				Grand Bahama Island (26.66°N, 78.32°W)		
2020-8	Flood	Flood (General)	Pakistan	Sindh Province (25.50°N, 69.00°E)	26.35	68.85
				Khyber Pakhtunkhwa Province (34.95°N, 72.33°E)		
				Balochistan Province (28.00°N, 67.00°E)		
2014-8	Mass movement	Landslide	Nepal	Jure Village (27.77°N, 85.87°E)	27.77	85.84
				Mankha Village (27.76°N, 85.83°E)		

*: Precise latitude-longitude coordinates are available for all earthquake events in EM-DAT.

2.3 Risk indices

Disaster risk assessments at a global or large scale commonly use indicator-based methods or statistical analyses of historical data (Gill and Malamud, 2014; Shi et al., 2016; Ming et al., 2015), whereas local and urban studies at smaller scales often rely on remote sensing-supported simulations (Chen et al., 2014). In this study, we adopt a hybrid approach that combines a global indicator-based index (WRI) with event statistics at the grid scale to construct the ARI.

In disaster risk assessment, there is broad consensus that risk results from the interaction between the hazard posed by a disaster and the vulnerability of the affected region (Koks et al., 2019; Koks et al., 2015; Little et al., 2023; Welle and Birkmann, 2015; Birkmann, 2007), often expressed as:

$$\text{Risk} = \text{Hazard} \times \text{Vulnerability}. \quad (1)$$

Equation (1) is a simplified schematic representation that highlights the joint influence of physical processes and socio-economic fragility. This basic formula has evolved into various forms to accommodate different dimensional requirements and methodological approaches. In many operational frameworks, a third component (Exposure) is explicitly included to reflect the population and assets at risk. For example, DRI expands the model to define risk as the product of hazard, population, and vulnerability (UNDP, 2004), while WRI characterizes the risk index as the geometric mean of exposure and vulnerability (Frege et al., 2023).

2.3.1 World Risk Index (reference index)

The WRI framework, published annually since 2011 through the World Risk Report (WRR), is particularly noteworthy for its alignment with current United Nations Office for Disaster Risk Reduction (UNDRR) terminology and its contemporary relevance (Mucke et al., 2011; Frege et al., 2023). In WRI, exposure quantifies an area's susceptibility to various hazards, primarily considering hazard intensity and population density (Frege et al., 2023). Vulnerability, on the other hand, is composed of sensitivity, lack of coping capacities, and lack of adaptive capacities (Frege et al., 2023), closely linked to socio-economic factors. WRI is expressed as follows:

$$\text{WRI} = \sqrt{E(P, D) \times V(S, L_1, L_2)}, \quad (2)$$

where E is exposure, V is vulnerability, P is number and share of the population regarding, D is intensity levels of natural hazards, S is susceptibility, L_1 is lack of coping capacities, and L_2 is lack of adaptive capacities (Frege et al., 2023).

WRR posits that the occurrence of disaster events is influenced both by severity of disaster impacts on society and vulnerability of society in responding to these impacts (Mucke et al., 2011). In other words, the risk level of disaster events depends on both natural processes and social capabilities (Frege et al., 2023). Building on this foundation, WRR specifically emphasizes that the countries most severely affected by disaster events often lack the social capability to cope with the negative impacts of such events due to previous disasters that have eroded their resilience (Frege et al., 2023). This underscores the importance of considering the accumulative effects of recent major disaster events when conducting risk assessments.

However, WRI only provides broad statistics of relevant populations from a perspective of vulnerable groups (Frege et al., 2023), represented by two indicators, "Internally displaced persons due to natural disasters" and "Population affected by disasters in the last 5 years". Furthermore, as discussed in Section 2.1, the definitions and estimates of these population indicators may not be reliable. Moreover, since the population data of WRI are updated based on the latest global census (Frege et al., 2023), which is not refreshed annually, may lead to the neglect of recent changes in the severity of hazards, and a delay in timeliness.

2.3.2 Accumulated Risk Index (proposed index)

In this study, WRI is not recomputed or modified. Instead, it is adopted as a country-level reference index and contextual weighting factor that encapsulates exposure and vulnerability conditions. The proposed ARI builds on WRI by combining it with the recent occurrence of major disaster events at the grid scale, using WRI as a scaling factor rather than as a quantity to be spatially aggregated on its own.

Building on the reference index introduced above, ARI is formulated as a grid-based measure that integrates recent major disaster events with country-level contextual information. Conceptually, ARI integrates two components: 1) the frequency of major disaster events (defined by the filtering strategy in Section 2.1) occurring within each latitude-longitude grid cell over the period 2013-2023; and 2) the country-level WRI value associated with each event, which adjusts for differences in exposure and vulnerability among affected regions. In this way, ARI emphasizes the short-term accumulation of high-impact shocks in contexts with varying underlying risk conditions. The expression is as follows:

$$ARI_j = \sum_{i=1}^{n_j} WRI_i \quad (n_j \geq 1), \quad (3)$$

where ARI_j represents the ARI of the selected region j , WRI_i represents the WRI of the country where the i -th major disaster event in region j took place, and n_j is the number of major disaster events that have occurred recently within region j . When n_j equals 0, it is assumed that the ARI of the region is also 0.

In the current implementation, all major events above the ≥ 50 fatalities threshold contribute equally to ARI, regardless of their exact death toll. This simplification avoids introducing additional uncertainty from severity weighting and allows a clearer interpretation of ARI as an index of recent accumulative disaster stress rather than a full description of all severity dimensions.

The selection of WRI as ARI's foundational framework is supported by four key considerations: 1) WRI maintains contemporary relevance through annual updates via WRR, ensuring continuous methodological evolution; 2) WRI's comprehensive framework of 100 indicators spans social, economic, political, and environmental dimensions (Frege et al., 2023; Mucke et al., 2022), effectively leveraging country-level data advantages; 3) WRI's exclusive focus on disaster risk encompasses diverse disaster types; 4) WRI's quantitative scoring system facilitates comparative analysis and further computational applications. In ARI, these advantages are retained while shifting the focus from long-term structural risk to the accumulative impacts of recent major events. Although WRI and the present study differ in their categorization of natural hazards, both concentrate on major natural hazards affecting large populations. Given the aggregate nature of WRI and the exploratory purpose of ARI, these differences in taxonomy are considered acceptable for the present analysis.

For grid cells intersecting multiple countries, each event is linked to the WRI of the country recorded in EM-DAT as part of the affected area. This event-level association allows ARI to reflect both the spatial distribution of recent major events and the country-specific risk context. To facilitate comparison with the original country-based WRI, an Equivalent WRI is also calculated at the grid scale by assigning each cell the maximum WRI of all countries overlapping the cell. This conservative choice ensures that the grid-level reference index reflects the highest background risk. Spatial patterns and contrasts between ARI and Equivalent WRI are presented in Section 3.2.

2.4 Spatial aggregation for ARI computation

Specific statistical calculations for ARI depend on the selection of region j , which enables for the possibility of using sub-national regions as basic assessment units. However, the choice of region size is critical. An excessively large region size diminishes the advantages of using latitude-longitude regions as assessment units. Conversely, an overly small size adversely affects the results in two ways: 1) Due to the extensive impact range of large-scale hazards, which can extend over thousands of square kilometers, it becomes challenging to adequately characterize hazard types (e.g. floods and storms) that affect large areas. This limitation inhibits an effective representation of the independence of regional disaster

events. 2) Relative errors will be amplified, leading to a decrease in the overall usability and reliability of data. Additionally, changes in exposure due to variations in population distribution and hazard zones over a given period will become more pronounced (Dilley, 2005), significantly affecting the timeliness of related data. Moreover, as disaster risk assessments become more refined at smaller scales (Feng et al., 2017; Smith et al., 2019), the pursuit of excessively small assessment unit sizes on a global scale clearly no longer meets practical application needs. Therefore, this study ultimately selects $5^{\circ} \times 5^{\circ}$ latitude-longitude grid as the minimum unit for regional division. This resolution provides a balance between global coverage, data reliability and compatibility with remote sensing applications. Robustness checks using alternative grid sizes ($2.5^{\circ} \times 2.5^{\circ}$ and $10^{\circ} \times 10^{\circ}$) are presented in Section 3.3.

2.5 Analytical workflow

To improve methodological coherence and clarify how the different components of this study are integrated, we provide a consolidated workflow summarizing the complete process from data acquisition to index construction and dataset development (Figure 1). The workflow consists of three sequential stages: 1) Identification of major disaster events: Disaster records for 2013-2023 are extracted from EM-DAT and filtered using the ≥ 50 fatalities threshold (Section 2.1). Each selected event is assigned a standardized representative coordinate (Section 2.2), forming the empirical basis for subsequent spatial analysis. 2) Construction of the ARI: For each $5^{\circ} \times 5^{\circ}$ grid cell, major disaster events are aggregated and weighted using country-level WRI values to compute ARI (Section 2.3). The choice of grid size and related sensitivity considerations are discussed in Section 2.4 and evaluated in Section 3.3. 3) Development of the remote sensing dataset: Grids with high ARI values, interpreted as hotspots of accumulated risk, are linked to sub-meter satellite imagery. Existing open-source data are compiled and supplemented where necessary to form the proposed dataset (Section 4). This structured workflow provides a unified view of how statistical disaster records, global risk indices, and remote sensing observations jointly contribute to the assessment of accumulated multi-hazard risks and the development of a complementary geospatial dataset.

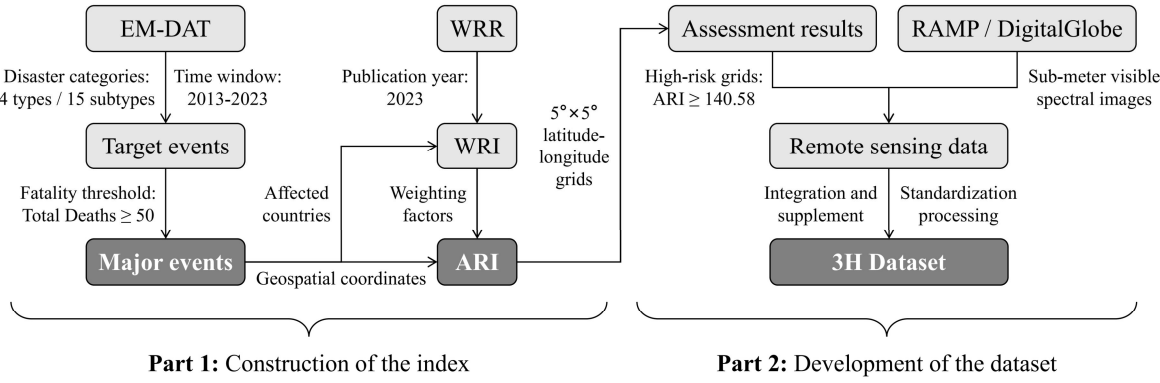


Figure 1: Methodology workflow diagram.

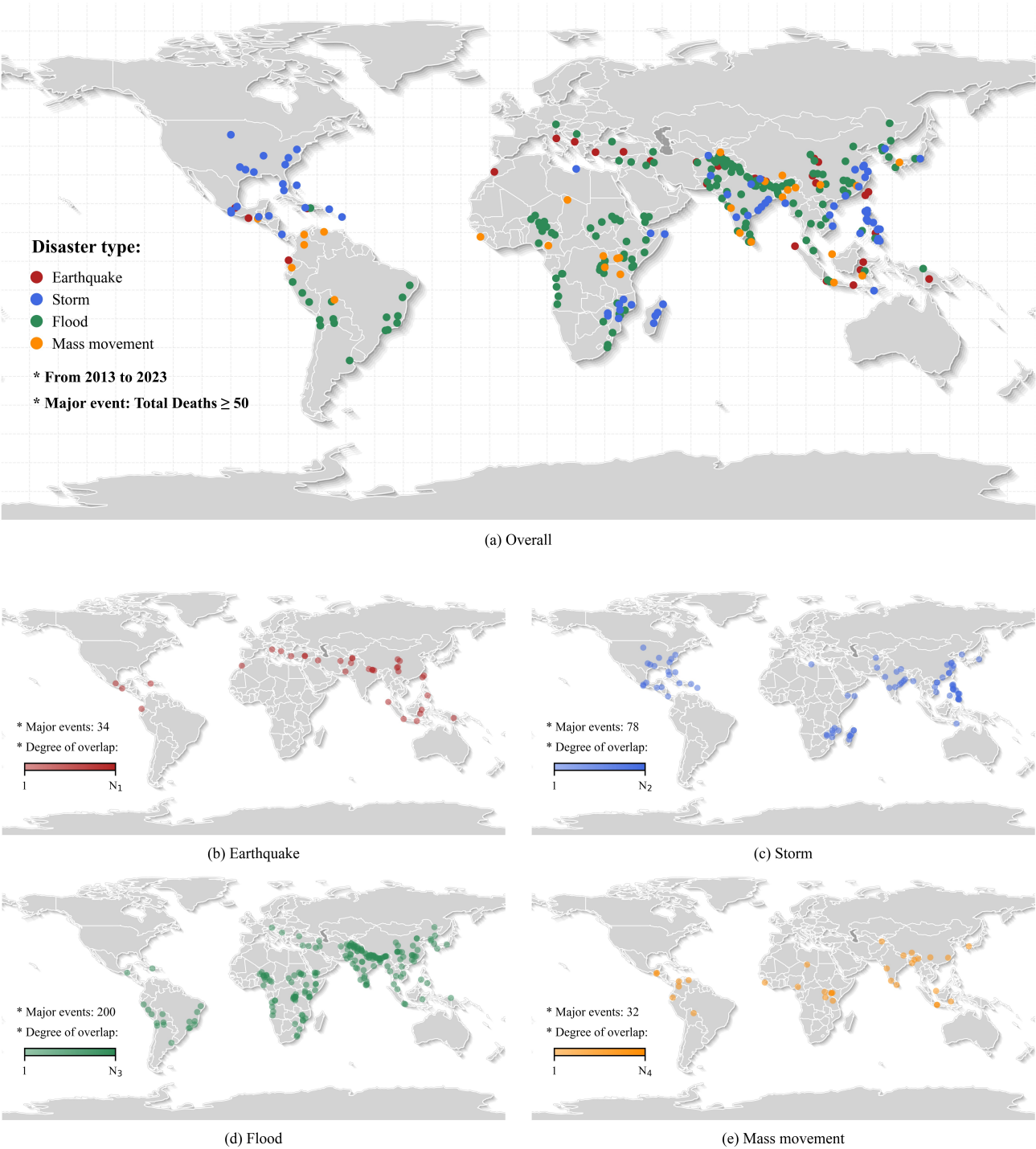
3 Results

3.1 Spatiotemporal characteristics of recent disaster events

Within the 2013-2023 study period, EM-DAT records 3217 target disaster events across four disaster types and fifteen disaster subtypes (Table 2). Applying the ≥ 50 fatalities criterion results in 344 major disaster events that form the empirical basis of this study. Among these, earthquakes, storms, floods and mass movements account for 9.9%, 22.7%, 58.1% and 9.3% of events, respectively. As estimated from the selected major events, these percentages provide an approximate indication of the relative contribution of different disaster types to recent high-fatality impacts at the global scale, indicating that floods dominate recent high-fatality disasters, followed by storms, while earthquakes and mass movements

contribute smaller but non-negligible shares.

The resulting spatial analysis is visualized in Figure 2, with panel (a) displaying the geographic distribution of all selected disaster events plotted against a global basemap from Natural Earth (<https://www.naturalearthdata.com>). Panels (b) through (e) present detailed distribution and frequency patterns for different disaster types, utilizing transparency in data point visualization and separate subplots to enhance the clarity of spatial patterns.



N₁-N₄: The maximum overlap degree of the data points, approximately represents the maximum frequency of major disaster events from 2013 to 2023.

Figure 2: Geographic spatial distribution of recent disaster events.

Overall, major disaster events exhibit marked spatial clustering rather than a random global distribution. High concentrations of events are observed along tectonically active belts and in monsoon-affected regions, particularly in and around South and Southeast Asia, as well as in parts of Central America. These clusters often extend across national borders, reflecting the fact that many large-scale hazards, such as riverine floods and tropical cyclones, inherently

transcend administrative boundaries. The observed patterns imply that assessments based solely on national units may obscure important cross-border and subnational variations in disaster occurrence. This provides empirical motivation for adopting a latitude-longitude grid as the basic assessment unit in the ARI, thereby aligning the spatial representation of risk more closely with the geographic footprint of major disaster events.

3.2 Global ARI distribution and hotspots

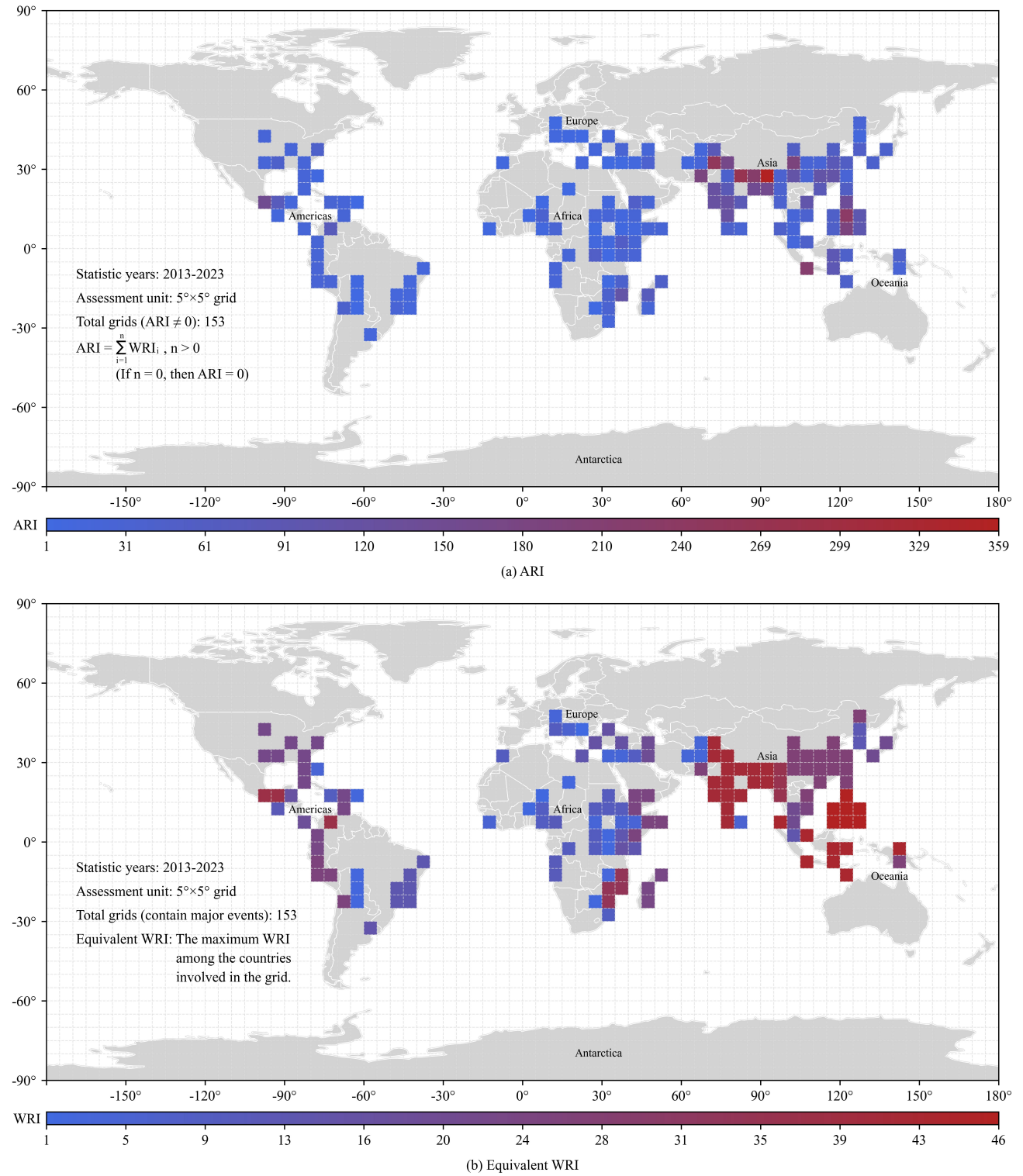


Figure 3: Global distribution of ARI and Equivalent WRI in 5°x5° latitude-longitude grids.

Using the 5°x5° latitude-longitude grid as the minimum spatial unit, ARI values are computed for all regions based on the occurrence of major disaster events and the corresponding country-level WRI values. Calculation results indicate that there are 153 grids with ARI≠0, accounting for 5.9% of the total grid cells (Figure 3(a)). High ARI values are predominantly

concentrated in Asia, especially in regions surrounding the Himalayas and along the coastal belts of South and Southeast Asia, where repeated major floods, storms and earthquakes have occurred within the past decade. In contrast, many other grids exhibit relatively low ARI levels. For example, the first quartile of non-zero ARI is 91, below which a large number of regions are characterized by limited accumulative impacts of major disasters during 2013-2023.

To facilitate comparison with country-level risk patterns, an Equivalent WRI is calculated for each grid cell by assigning the maximum WRI value among all countries intersecting the grid (Section 2.3.2). The resulting Equivalent WRI distribution is shown in Figure 3(b). While both ARI and Equivalent WRI highlight elevated risk in parts of Asia, their spatial contrasts differ: ARI produces a more pronounced differentiation between high- and low-risk grids, particularly in areas where multiple major disasters have clustered in recent years. This suggests that the incorporation of recent event accumulation can sharpen spatial contrasts relative to long-term, country-level indices.

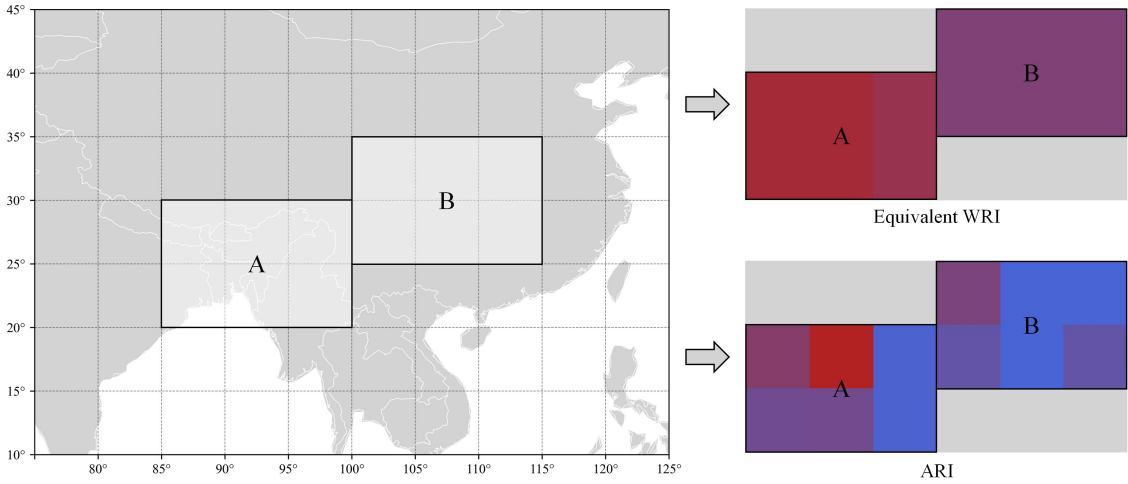


Figure 4: Local zoom-in comparison of ARI and Equivalent WRI in 5°×5° latitude-longitude grids.

To improve interpretability beyond the global maps, Figure 4 provides a regional zoom-in corresponding to the Himalayan belt and South-Southeast Asia where high ARI grids cluster in Figure 3(a). The figure is designed for a grid-aligned comparison: the full 5°×5° gridlines are shown in the regional window, and the two highlighted sub-windows (A and B) are reproduced on the right as actual cell-by-cell mosaics for Equivalent WRI and ARI using the same colour scales as Figure 3.

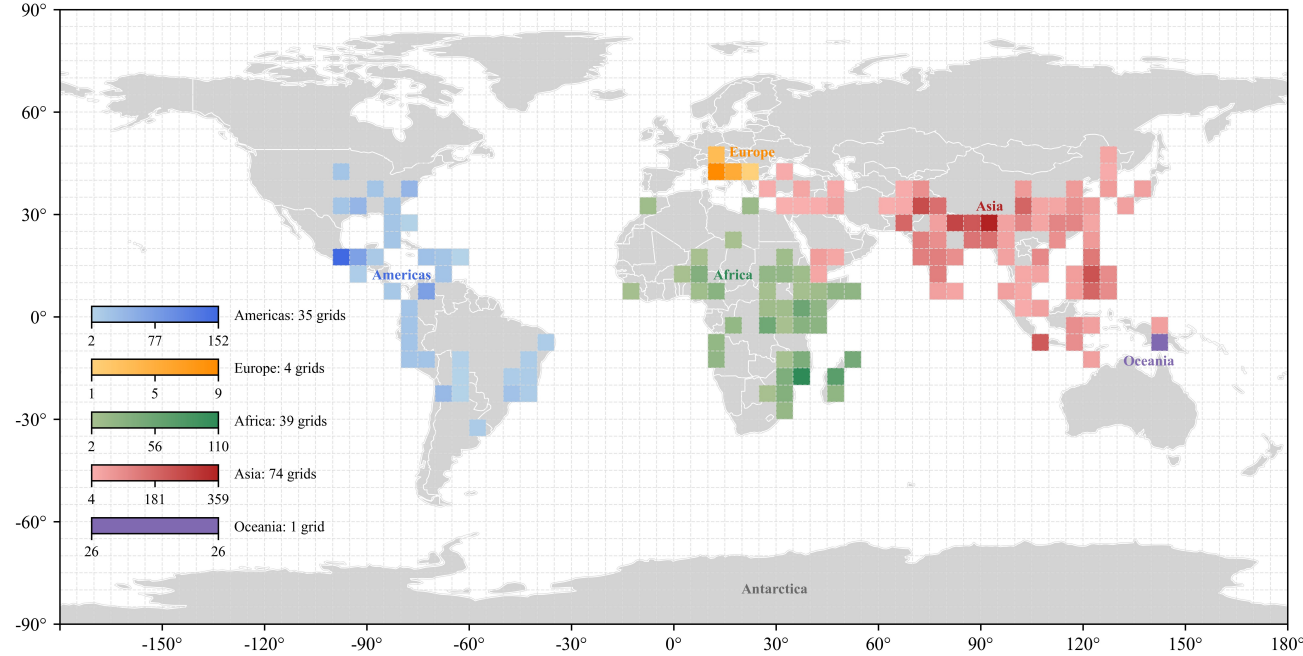
Two contrasting situations are illustrated. In Window A, which spans multiple countries, Equivalent WRI mainly reflects country-level background differences, whereas ARI further differentiates neighbouring 5°×5° cells according to the spatial concentration of recent major events within the same transboundary corridor. In Window B, which lies entirely within China, Equivalent WRI becomes spatially uniform by construction, while ARI still exhibits marked intra-national heterogeneity, indicating sub-national hotspots associated with recent event accumulation. Together, the zoom-in comparison is consistent with the interpretation drawn from Figure 3 that incorporating near-term event accumulation can sharpen spatial contrasts relative to long-term, country-level reference indices, particularly along transboundary hazard corridors and within large countries where sub-national variability is important.

To further examine regional variability, ARI results are grouped by continental plates (Americas, Europe, Africa, Asia and Oceania) according to EM-DAT's geographic partitioning labels (Delforge et al., 2025). Figure 5 displays the distribution of ARI across these continents. Asia clearly dominates in terms of both the number of non-zero grids and the magnitude of ARI values, reflecting the combined influence of high hazard exposure and large populations in many developing countries. In other continents, non-zero ARI grids are fewer and generally of lower magnitude, although localized clusters of high ARI can still be identified, for instance in parts of Central America. The longitude-latitude grids are ranked according to ARI statistical results, and the detailed information of each grid is shown in Table A1 in the Appendix A.

To identify areas that merit particular attention in risk reduction and humanitarian planning, a subset of high-risk grids is

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defined. Following the WRI scale, the threshold is set to three times the maximum WRI value (46.86), corresponding to $ARI \geq 140.58$. Under this criterion, high-risk grids account for 9.2% of all non-zero ARI grids (Figure 6). Based on their geographic coordinates, these high-risk grids involve ten countries: India, China, Pakistan, the Philippines, Nepal, Bhutan, Indonesia, Myanmar, Bangladesh and Mexico. All of these are developing countries characterized by high population density, relatively weak infrastructure and unequal distribution of social resources (Koks et al., 2019; Rentschler et al., 2022; Berlemann et al., 2018). The identification of these high-risk grids provides a focused spatial framework for subsequent remote sensing data integration (Section 4).



315

Figure 5: Global distribution of ARI in 5°x5° latitude-longitude grids within continental plates.

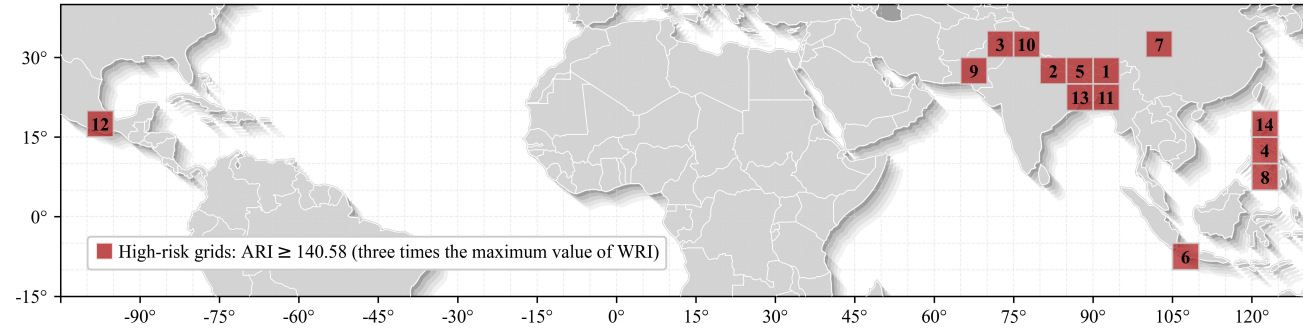


Figure 6: Spatial distribution of high-risk grids.

3.3 Validation and robustness checks

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Given that ARI is a newly proposed index, it is important to assess the robustness of its spatial patterns with respect to key methodological choices. This section examines the sensitivity of ARI to the fatality threshold used to define major disaster events and the spatial resolution of the latitude-longitude grids. These analyses are intended to evaluate whether the main spatial patterns identified in Sections 3.1 and 3.2 are stable under reasonable variations.

3.3.1 Sensitivity to the fatality threshold

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The baseline ARI configuration uses a threshold of ≥ 50 fatalities (Total Deaths) to select major disaster events (Section 2.1). To test the sensitivity of ARI to this choice, alternative thresholds of 40, 60 and 70 fatalities are considered. For each threshold, the number of major events and the ARI values of grids are recalculated. Table 4 summarizes the total number

of major events and the top 10 high-ARI grids identified under each scenario, together with their rankings under the baseline threshold.

Table 4: Comparison of ARI results under different thresholds (40, 60, and 70 fatalities).

Fatality threshold	Major disaster events	High-risk grids (top 10)					
		ARI ranking	Baseline ranking	Latitude range (°)	Longitude range (°)	Region	ARI
40	406	1	1	25 ~ 30	90 ~ 95	Asia	359.26
		2	2	25 ~ 30	80 ~ 85	Asia	311.2
		3	3	30 ~ 35	70 ~ 75	Asia	306.02
		4	5	25 ~ 30	85 ~ 90	Asia	268.51
		5	10	30 ~ 35	75 ~ 80	Asia	249.12
		6	4	10 ~ 15	120 ~ 125	Asia	234.3
		7	14	15 ~ 20	120 ~ 125	Asia	234.3
		8	6	-10 ~ -5	105 ~ 110	Asia	217.5
		9	7	30 ~ 35	100 ~ 105	Asia	216.8
		10	8	5 ~ 10	120 ~ 125	Asia	187.44
60	282	1	1	25 ~ 30	90 ~ 95	Asia	276.22
		2	2	25 ~ 30	80 ~ 85	Asia	269.68
		3	3	30 ~ 35	70 ~ 75	Asia	253.12
		4	4	10 ~ 15	120 ~ 125	Asia	234.3
		5	9	25 ~ 30	65 ~ 70	Asia	185.15
		6	6	-10 ~ -5	105 ~ 110	Asia	174
		7	10	30 ~ 35	75 ~ 80	Asia	166.08
		8	7	30 ~ 35	100 ~ 105	Asia	162.6
		9	11	20 ~ 25	90 ~ 95	Asia	159.55
		10	5	25 ~ 30	85 ~ 90	Asia	155.61
70	242	1	1	25 ~ 30	90 ~ 95	Asia	234.7
		2	4	10 ~ 15	120 ~ 125	Asia	234.3
		3	2	25 ~ 30	80 ~ 85	Asia	228.16
		4	3	30 ~ 35	70 ~ 75	Asia	200.22
		5	9	25 ~ 30	65 ~ 70	Asia	158.7
		6	5	25 ~ 30	85 ~ 90	Asia	155.61
		7	8	5 ~ 10	120 ~ 125	Asia	140.58
		8	7	30 ~ 35	100 ~ 105	Asia	135.5
		9	17	15 ~ 20	75 ~ 80	Asia	124.56
		10	11	20 ~ 25	90 ~ 95	Asia	118.03

As expected, lowering the threshold to 40 fatalities increases the number of major events to 406, whereas raising it to 60 and 70 fatalities reduces the counts to 282 and 242, respectively. Despite these changes in absolute event numbers and ARI magnitudes, the spatial pattern of high-ARI grids remains broadly consistent. In all scenarios, the highest-ranking grids are located in South and Southeast Asia, particularly in regions covering northern India, Bangladesh and the Himalayan belt. Moreover, many of the top 10 grids under the alternative thresholds coincide with those in the baseline configuration, often with only minor changes in rank. This indicates that the identification of key high-risk areas is not strongly dependent on the exact choice of fatality threshold, although the absolute ARI values vary with the number of included events.

3.3.2 Sensitivity to grid resolution

The baseline ARI computation adopts 5°×5° latitude-longitude grids as the minimum spatial unit (Section 2.4). To evaluate

the influence of spatial resolution, additional ARI maps are generated using finer ($2.5^{\circ}\times 2.5^{\circ}$) and coarser ($10^{\circ}\times 10^{\circ}$) grids.

Figure 7 compares the resulting ARI distributions for the two resolutions.

When a finer $2.5^{\circ}\times 2.5^{\circ}$ grid is used, the number of non-zero ARI cells increases, and localized variations within large countries become more pronounced. Conversely, the $10^{\circ}\times 10^{\circ}$ grid leads to fewer non-zero cells and smoother spatial gradients. However, across all three resolutions, the main clusters of high ARI consistently appear in the same broad regions, namely South and Southeast Asia and parts of Central America. The locations of the most prominent hotspots remain stable, even though their exact shapes and ARI magnitudes change with grid size. This suggests that ARI is robust in identifying the principal geographic concentrations of accumulated disaster risk at the global scale.

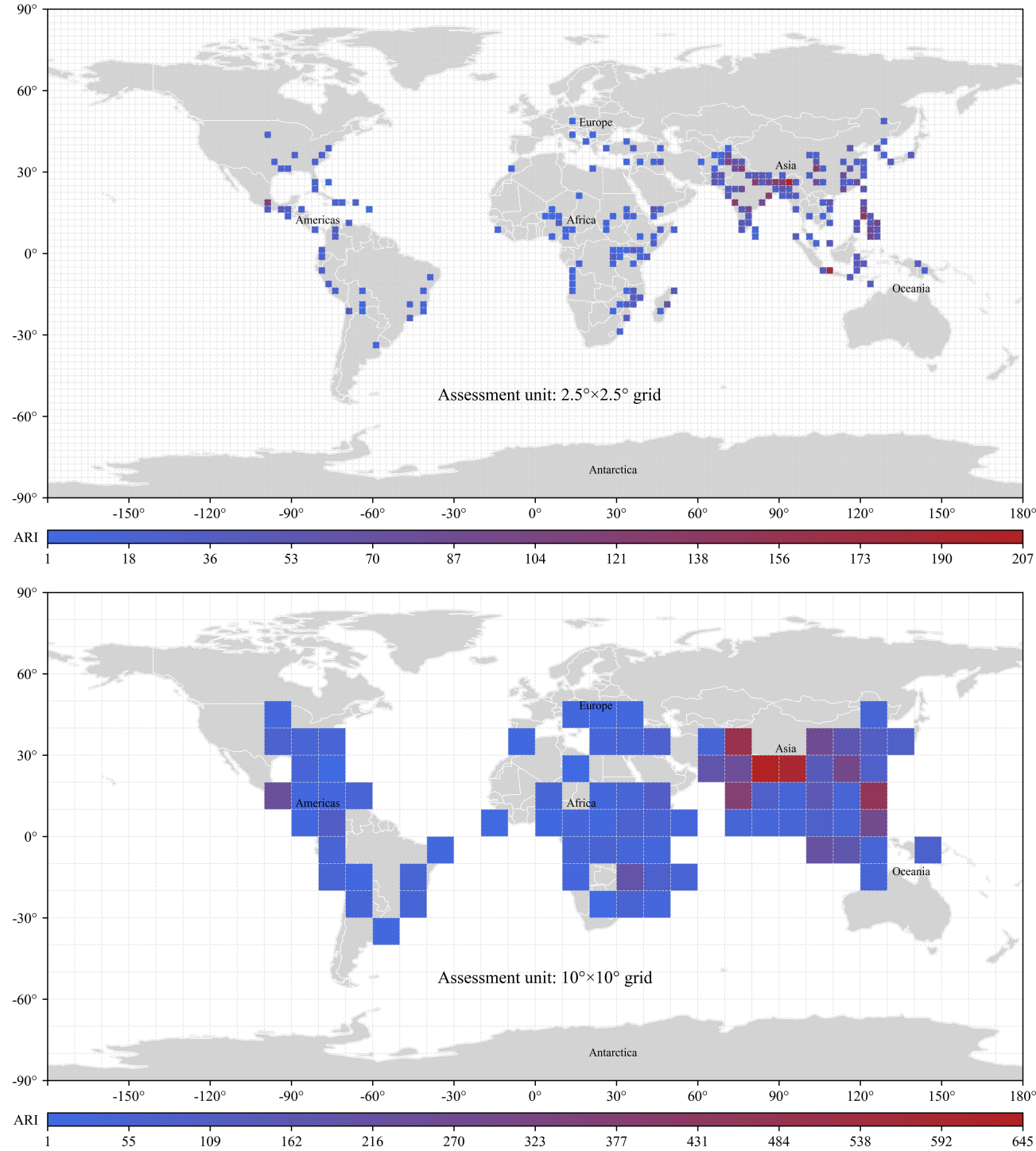


Figure 7: Comparison of ARI results under different spatial grids ($2.5^{\circ}\times 2.5^{\circ}$ and $10^{\circ}\times 10^{\circ}$).

Taken together, the sensitivity analyses on the fatality threshold and grid resolution indicate that the main spatial features of ARI, especially the identification of high-risk clusters in developing regions, are relatively insensitive to reasonable

variations in key methodological parameters. ARI is therefore suitable for comparative hotspot identification at the global scale, while detailed local interpretation should consider the uncertainties discussed in Section 5.

4 Remote sensing data integration for ARI hotspots

The ARI results presented in Section 3.2 identify high-risk latitude-longitude grids where recent major disaster events have accumulated and where local resilience may have been significantly eroded. These grids provide spatial focal points for detailed risk assessment and management at finer scales. At such scales, remote sensing technology is widely recognized as a key tool for mapping exposed assets and post-disaster damage.

However, high-resolution remote sensing data, particularly sub-meter visible spectral imagery, are still predominantly obtained through commercial purchases and remain costly for many institutions, especially in developing countries. Existing open-source datasets tend to focus on large cities or specific crisis events, often in developed regions, rather than on systematically identified global risk hotspots. In addition, open-source data from different providers vary in image type, size, and other attributes, complicating direct integration and application. Overall, the lack of specific, consistent and readily accessible high-resolution imagery in high-risk but data-scarce regions constitutes a major bottleneck for advancing disaster risk assessment and management.

In this context, the role of remote sensing in the present study is complementary rather than strictly validating: ARI is used to highlight high-risk grids, and remote sensing data are then integrated and supplemented for these grids to create an open-source dataset that can support future damage detection, risk monitoring and model development. This approach establishes a bridge between macro-scale statistical risk assessment and micro-scale Earth observation applications.

4.1 Data sources and spatial coverage

Based on the ARI-derived high-risk grids (Section 3.2), an extensive review of existing open-source remote sensing datasets was conducted to identify sub-metre visible spectral imagery covering these grids. Figure 8 shows the spatial distribution of all available data. Two primary data sources were used: 1) RAMP Building Footprint Training Dataset, developed under the WHO-supported DevGlobal initiative (<https://rampml.global>). 2) DigitalGlobe Open Data Program, launched by the commercial remote sensing company Maxar (<https://www.maxar.com/open-data>).

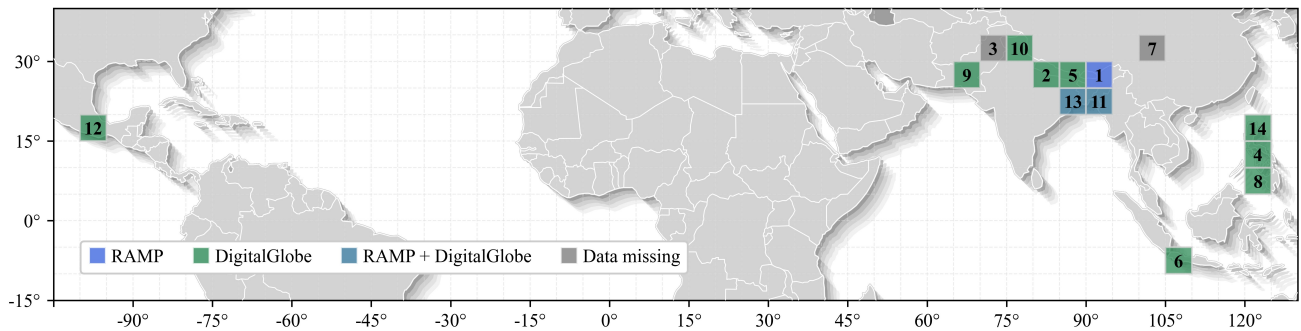


Figure 8: Spatial distribution of existing data for high-risk grids.

Table 5: Detailed information of all data for high-risk grids.

Grid	Data source	Part name from data source	Latitude center (°)	Longitude center (°)	Resolution (m)
1	RAMP	Sylhet, Bangladesh	24.96	91.68	0.27
2	DigitalGlobe	Nepal Earthquake Nov. 2023	28.86	82.21	0.31
3	Supplement	-	33.09	74.79	0.30
4	DigitalGlobe	Typhoon Goni	13.18	123.74	0.33 ~ 0.53
	DigitalGlobe	Typhoon Vamco	11.61	122.83	0.34 ~ 0.50

5	DigitalGlobe	North India Floods	27.55	88.40	0.31
6	DigitalGlobe	Sunda Strait Tsunami	-6.01	105.80	0.49
	DigitalGlobe	Indonesia Earthquake 2022	-6.87	107.06	0.31
7	Supplement	-	30.46	104.02	0.30
8	DigitalGlobe	Typhoon Vamco	11.61	122.83	0.34 ~ 0.50
9	DigitalGlobe	Pakistan Flooding	30.15	70.08	0.31
	DigitalGlobe	Pakistan Earthquake	30.12	67.98	0.45 ~ 0.55
10	DigitalGlobe	Uttarakhand-Flooding	30.63	79.63	0.45 ~ 0.51
11	RAMP	Sylhet, Bangladesh	24.96	91.68	0.27
	RAMP	Chittagong, Bangladesh	21.24	92.18	0.40
	RAMP	Cox's Bazar, Bangladesh	21.43	91.99	0.35
	RAMP	Dhaka, Bangladesh	23.81	90.41	0.30
	RAMP	Barishal, Bangladesh	22.71	90.35	0.38
	DigitalGlobe	Bay of Bengal Cyclone Mocha 2023	20.82	92.40	0.31
	DigitalGlobe	COVID19 Bangladesh	22.38	91.30	0.29 ~ 0.54
	DigitalGlobe	Cyclone Fani	21.60	87.57	0.28 ~ 0.54
12	DigitalGlobe	Southern Mexico Earthquake	16.63	-94.14	0.42 ~ 0.50
13	RAMP	Jashore, Bangladesh	23.15	89.16	0.34
	DigitalGlobe	Cyclone Fani	21.60	87.57	0.28 ~ 0.54
14	DigitalGlobe	Typhoon Vongfong	15.79	121.40	0.29 ~ 0.48
	DigitalGlobe	Super Typhoon Mangkhut	17.87	121.43	0.28 ~ 0.53

Using these sources, sub-metre visible spectral images were compiled for the set of high-risk grids identified by ARI. Table 5 summarizes the detailed information for each grid. Most grids are covered by one or several DigitalGlobe crisis datasets, while some, especially those in Bangladesh, benefit from multiple RAMP tiles that provide dense coverage of urban and peri-urban areas.

4.2 Supplementing data gaps in high-risk grids

Despite the relatively broad coverage provided by RAMP and DigitalGlobe, two high-risk grids (Grids 3 and 7 in Table 5) lack suitable open-source imagery. To address these gaps, additional visible spectral satellite images were acquired and processed specifically for these grids. For each of the two grids, imagery covering a rectangular area of approximately 50 km² was obtained, resulting in 100 km² of supplementary data in total. The centre of each acquisition area was chosen to coincide with the geographic location of the major disaster event with the maximum “Total Deaths” in that grid, thereby ensuring that the supplemented imagery is directly relevant to the most severe recorded impacts. The supplemented images were selected to match, as closely as possible, the spatial resolution and spectral characteristics of the existing open-source datasets, so that they could be seamlessly integrated into a unified dataset.

4.3 Standardization and construction of the 3H Dataset

To create a coherent and user-friendly dataset, all imagery from RAMP, DigitalGlobe and the supplementary acquisitions was subjected to a common standardization workflow. First, scenes were visually inspected and tiles with severe artefacts, cloud contamination or obvious irrelevance to built-up areas were removed. The remaining images were then cropped and tiled into fixed-size patches of 256×256 pixels. All tiles were stored in TIF format and annotated with the corresponding grid identifier and data source. This procedure was applied consistently across the 14 high-risk grids.

The final normalized dataset contains 7,583,094 TIF images, each of size 256×256 pixels, with spatial resolutions ranging from 0.27 m to 0.54 m. All tiles are located within the 14 high-risk grids identified by ARI and span ten developing

400 countries. Figure 9 provides representative examples of the imagery, illustrating the diversity of urban forms, building densities and environmental contexts captured by the dataset.

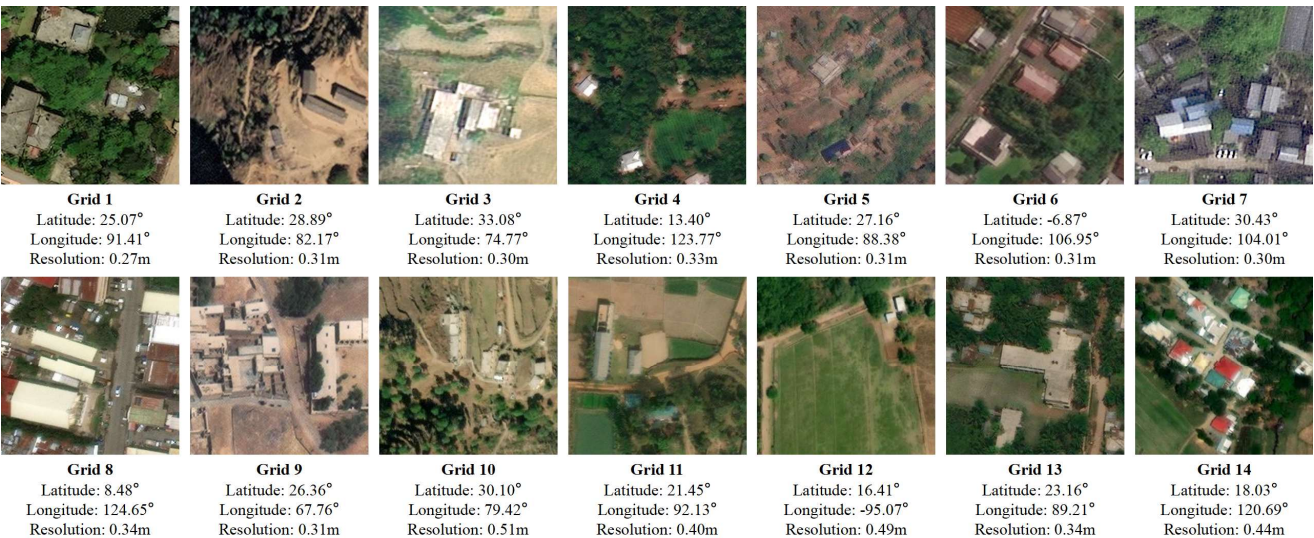


Figure 9: Examples of data in 3H Dataset. Most of the materials are collected and prepared from RAMP and DigitalGlobe, while the remaining data are acquired and produced by the authors.

405 The final data compilation for each high-risk grid is summarized in Table A2 in the Appendix A. This integrated dataset is named the “3H Dataset”, referring to **H**igh spatial-resolution remote sensing imagery within latitude-longitude grids of **H**igh accumulated risk caused by disaster events with **H**igh mortality rates. By focusing explicitly on ARI-identified hotspots in developing countries and providing standardized imagery, the 3H Dataset is expected to help mitigate several key challenges faced by these regions, including the scarcity of high-quality data, the high cost of commercial imagery and

410 limited access to consistent data sources. In turn, it is intended to support future research and to encourage wider application of remote sensing technologies in multi-disaster risk assessment and management.

5 Discussion

ARI highlights areas where high-fatality disaster events have clustered within a relatively short period and where underlying country-level exposure and vulnerability conditions amplify their impacts. The index does not aim to replicate

415 or replace long-term structural risk metrics such as WRI, but to provide a complementary perspective focused on recent accumulative shocks. Compared with a grid-based equivalent of the WRI, ARI yields sharper contrasts between hotspots and low-activity areas, indicating that near-term accumulative effects can significantly modify the perceived risk pattern at sub-national and transboundary scales. The results therefore underscore the value of combining event-driven metrics with background socio-economic conditions for identifying areas where resilience may have deteriorated more rapidly than

420 long-term indices would suggest.

Sensitivity analyses show that ARI is relatively robust to reasonable changes in both the fatality threshold and grid resolution. While absolute ARI values vary, the spatial configuration of high-risk grids remains stable, confirming that ARI is more suitable for hotspot identification than for precise quantitative ranking. Nevertheless, several methodological limitations should be acknowledged: 1) Event filtering: Using a ≥ 50 fatality threshold excludes smaller but potentially

425 accumulative events to reduce under-reporting bias and improve international comparability. 2) Spatial simplification: The assignment of a single representative coordinate per event inevitably simplifies complex hazard footprints, particularly for floods and storms with broad spatial extents. 3) Data dependency: ARI inherits inherent uncertainties from EM-DAT (e.g., reporting heterogeneity) and WRI (e.g., indicator transparency). Thus, ARI should be interpreted as a relative index of recent accumulative risk, best complemented by local datasets or expert analysis in operational decision-making.

Both EM-DAT and WRI provide harmonised global datasets, yet gaps and inconsistencies remain unavoidable. The standardization of textual location descriptions into point coordinates reduces heterogeneity but cannot eliminate spatial uncertainty in extended-impact events. Likewise, while WRI provides a consolidated view of exposure and vulnerability, some underlying datasets are updated asynchronously and are not fully documented. Because ARI combines event occurrence with WRI only as a contextual weighting factor, rather than spatially interpolating WRI, its results should be read as relative indications of where recent high-fatality events intersect with risk contexts, not as precise estimates of absolute risk levels.

Despite these caveats, the combined ARI-remote sensing framework offers practical value. For policy and humanitarian actors, ARI can help flag areas where repeated high-impact events may have eroded resilience and where more detailed assessments and targeted support are warranted. For the scientific community, the 3H Dataset provides standardized, sub-metre imagery for ARI hotspots in developing countries, lowering the barrier for remote sensing-based studies on damage detection, exposure mapping and recovery monitoring.

Future work could extend ARI by testing composite severity indicators when data quality allows, exploring alternative risk indices alongside WRI, and applying temporal weighting schemes to relate recent accumulative patterns to longer-term trends. Improved geocoding and the use of hazard footprints derived from Earth observation would support refined spatial units in selected regions. Closer coupling between ARI outputs and observed damage or recovery trajectories would also help to evaluate and further develop accumulated risk indicators under changing climate and socio-economic conditions.

6 Conclusions

This study advances the field of disaster risk assessment by combining country-level and geographic grid analyses while emphasizing recent accumulated disaster impacts and supporting remote sensing applications. The novel ARI defined in this paper is derived from an in-depth examination of major disaster events. The results reveal pronounced spatial clustering of earthquakes, storms, floods, and mass movements during 2013-2023, particularly across the Himalayan region and South-Southeast Asia. Compared with the long-term WRI, ARI provides sharper spatial contrasts and highlights sub-national hotspots where repeated shocks may have accelerated resilience loss. While not a replacement for structural risk indices, ARI offers a complementary perspective focused on near-term accumulative impacts. Based on ARI-identified hotspots, this study further develops the 3H Dataset, comprising over 7.5 million standardized sub-metre remote sensing image tiles across fourteen high-risk grids in ten developing countries. The dataset helps mitigate persistent barriers faced by these countries in conducting disaster risk assessment and management. In parallel, this open-source dataset aims to encourage greater scholarly attention to disaster risk research in developing countries and to promote the application of remote sensing technology in related fields.

Appendix A

Table A1: Detailed information of 153 grids (ARI≠0).

ARI ranking	Latitude range (°)	Longitude range (°)	Region	ARI	Equivalent WRI
1	25 ~ 30	90 ~ 95	Asia	359.26	41.52
2	25 ~ 30	80 ~ 85	Asia	269.68	41.52
3	30 ~ 35	70 ~ 75	Asia	253.12	41.52
4	10 ~ 15	120 ~ 125	Asia	234.3	46.86
5	25 ~ 30	85 ~ 90	Asia	224.42	41.52
6	-10 ~ -5	105 ~ 110	Asia	217.5	43.5
7	30 ~ 35	100 ~ 105	Asia	189.7	27.1

8	5 ~ 10	120 ~ 125	Asia	187.44	46.86
9	25 ~ 30	65 ~ 70	Asia	185.15	41.52
10	30 ~ 35	75 ~ 80	Asia	166.08	41.52
11	20 ~ 25	90 ~ 95	Asia	159.55	41.52
12	15 ~ 20	-100 ~ -95	Americas	152.68	38.17
13	20 ~ 25	85 ~ 90	Asia	151.85	41.52
14	15 ~ 20	120 ~ 125	Asia	140.58	46.86
15	10 ~ 15	75 ~ 80	Asia	124.56	41.52
16	15 ~ 20	70 ~ 75	Asia	124.56	41.52
17	15 ~ 20	75 ~ 80	Asia	124.56	41.52
18	20 ~ 25	70 ~ 75	Asia	124.56	41.52
19	-20 ~ -15	35 ~ 40	Africa	110.17	34.61
20	25 ~ 30	100 ~ 105	Asia	108.4	27.1
21	25 ~ 30	110 ~ 115	Asia	108.4	27.1
22	25 ~ 30	115 ~ 120	Asia	108.4	27.1
23	15 ~ 20	105 ~ 110	Asia	102.98	27.1
24	10 ~ 15	125 ~ 130	Asia	93.72	46.86
25	5 ~ 10	125 ~ 130	Asia	93.72	46.86
26	-10 ~ -5	115 ~ 120	Asia	87	43.5
27	-5 ~ 0	115 ~ 120	Asia	87	43.5
28	15 ~ 20	80 ~ 85	Asia	83.04	41.52
29	20 ~ 25	75 ~ 80	Asia	83.04	41.52
30	20 ~ 25	110 ~ 115	Asia	81.3	27.1
31	30 ~ 35	115 ~ 120	Asia	81.3	27.1
32	35 ~ 40	70 ~ 75	Asia	80.03	27.1
33	5 ~ 10	-75 ~ -70	Americas	75.28	37.64
34	15 ~ 20	-95 ~ -90	Americas	73.3	38.17
35	-20 ~ -15	45 ~ 50	Africa	70.77	23.59
36	0 ~ 5	35 ~ 40	Africa	54.84	13.71
37	20 ~ 25	120 ~ 125	Asia	54.2	27.1
38	30 ~ 35	120 ~ 125	Asia	54.2	27.1
39	35 ~ 40	100 ~ 105	Asia	54.2	27.1
40	35 ~ 40	115 ~ 120	Asia	54.2	27.1
41	-5 ~ 0	25 ~ 30	Africa	53.05	16.08
42	35 ~ 40	125 ~ 130	Asia	49.09	12.75
43	15 ~ 20	40 ~ 45	Asia	48.78	24.39
44	-15 ~ -10	50 ~ 55	Africa	47.18	23.59
45	5 ~ 10	115 ~ 120	Asia	46.86	46.86
46	10 ~ 15	115 ~ 120	Asia	46.86	46.86
47	30 ~ 35	-95 ~ -90	Americas	44.94	22.47
48	35 ~ 40	-80 ~ -75	Americas	44.94	22.47
49	-15 ~ -10	120 ~ 125	Asia	43.5	43.5
50	-5 ~ 0	120 ~ 125	Asia	43.5	43.5
51	-5 ~ 0	140 ~ 145	Asia	43.5	43.5
52	0 ~ 5	105 ~ 110	Asia	43.5	43.5
53	5 ~ 10	95 ~ 100	Asia	43.5	43.5
54	30 ~ 35	130 ~ 135	Asia	41.72	20.86

55	35 ~ 40	135 ~ 140	Asia	41.72	20.86
56	5 ~ 10	75 ~ 80	Asia	41.52	41.52
57	25 ~ 30	75 ~ 80	Asia	41.52	41.52
58	-15 ~ -10	35 ~ 40	Africa	40.95	34.61
59	-20 ~ -15	30 ~ 35	Africa	39.65	34.61
60	-25 ~ -20	-70 ~ -65	Americas	39.61	14.88
61	30 ~ 35	45 ~ 50	Asia	39.44	19.72
62	15 ~ 20	95 ~ 100	Asia	36.16	36.16
63	20 ~ 25	95 ~ 100	Asia	36.16	36.16
64	25 ~ 30	95 ~ 100	Asia	36.16	41.52
65	10 ~ 15	5 ~ 10	Africa	36.15	9.17
66	10 ~ 15	105 ~ 110	Asia	35.37	24.39
67	-25 ~ -20	30 ~ 35	Africa	34.61	34.61
68	-5 ~ 0	35 ~ 40	Africa	29.79	16.08
69	5 ~ 10	80 ~ 85	Asia	29.6	5.92
70	5 ~ 10	10 ~ 15	Africa	29.49	11.15
71	15 ~ 20	-75 ~ -70	Americas	29.01	12.92
72	35 ~ 40	35 ~ 40	Asia	28.41	16.17
73	-5 ~ 0	40 ~ 45	Africa	27.42	25.09
74	25 ~ 30	105 ~ 110	Asia	27.1	27.1
75	25 ~ 30	120 ~ 125	Asia	27.1	27.1
76	30 ~ 35	105 ~ 110	Asia	27.1	27.1
77	30 ~ 35	110 ~ 115	Asia	27.1	27.1
78	45 ~ 50	125 ~ 130	Asia	27.1	28.2
79	-25 ~ -20	-50 ~ -45	Americas	26.94	13.47
80	-10 ~ -5	140 ~ 145	Oceania	26.3	43.5
81	-15 ~ -10	-80 ~ -75	Americas	25.55	25.55
82	-15 ~ -10	-75 ~ -70	Americas	25.55	25.55
83	-10 ~ -5	-80 ~ -75	Americas	25.55	25.55
84	0 ~ 5	40 ~ 45	Africa	25.09	25.09
85	5 ~ 10	45 ~ 50	Africa	25.09	25.09
86	5 ~ 10	50 ~ 55	Africa	25.09	25.09
87	10 ~ 15	40 ~ 45	Asia	24.39	24.39
88	15 ~ 20	45 ~ 50	Asia	24.39	24.39
89	-25 ~ -20	45 ~ 50	Africa	23.59	23.59
90	-5 ~ 0	-80 ~ -75	Americas	23.58	37.64
91	0 ~ 5	-80 ~ -75	Americas	23.58	37.64
92	10 ~ 15	-70 ~ -65	Americas	23.47	23.47
93	15 ~ 20	-70 ~ -65	Americas	22.47	22.47
94	20 ~ 25	-85 ~ -80	Americas	22.47	7.76
95	30 ~ 35	-100 ~ -95	Americas	22.47	22.47
96	30 ~ 35	-85 ~ -80	Americas	22.47	22.47
97	35 ~ 40	-90 ~ -85	Americas	22.47	22.47
98	40 ~ 45	-100 ~ -95	Americas	22.47	22.47
99	25 ~ 30	-85 ~ -80	Americas	22.47	22.47
100	-15 ~ -10	10 ~ 15	Africa	22.08	11.04
101	5 ~ 10	100 ~ 105	Asia	21.09	24.39

102	10 ~ 15	100 ~ 105	Asia	21.09	24.39
103	-10 ~ -5	10 ~ 15	Africa	20.77	11.04
104	10 ~ 15	25 ~ 30	Africa	20.54	10.27
105	10 ~ 15	30 ~ 35	Africa	20.54	10.27
106	30 ~ 35	65 ~ 70	Asia	20.1	26.45
107	35 ~ 40	45 ~ 50	Asia	19.72	19.72
108	-5 ~ 0	15 ~ 20	Africa	19.46	9.73
109	5 ~ 10	-85 ~ -80	Americas	18.82	18.82
110	-30 ~ -25	30 ~ 35	Africa	18.28	34.61
111	15 ~ 20	-90 ~ -85	Americas	16.79	38.17
112	35 ~ 40	25 ~ 30	Asia	16.17	16.17
113	40 ~ 45	30 ~ 35	Asia	16.17	28.2
114	35 ~ 40	65 ~ 70	Asia	16.08	4.02
115	-35 ~ -30	-60 ~ -55	Americas	14.88	14.88
116	0 ~ 5	100 ~ 105	Asia	14.04	43.5
117	30 ~ 35	20 ~ 25	Africa	13.93	17.76
118	-25 ~ -20	-45 ~ -40	Americas	13.47	13.47
119	-20 ~ -15	-50 ~ -45	Americas	13.47	13.47
120	-20 ~ -15	-45 ~ -40	Americas	13.47	13.47
121	-15 ~ -10	-45 ~ -40	Americas	13.47	13.47
122	-10 ~ -5	-40 ~ -35	Americas	13.47	13.47
123	40 ~ 45	125 ~ 130	Asia	12.75	27.1
124	10 ~ 15	-95 ~ -90	Americas	11.71	38.17
125	10 ~ 15	35 ~ 40	Africa	10.27	10.27
126	15 ~ 20	30 ~ 35	Africa	10.27	10.27
127	40 ~ 45	10 ~ 15	Europe	9.97	9.97
128	30 ~ 35	-10 ~ -5	Africa	9.96	9.96
129	0 ~ 5	25 ~ 30	Africa	9.73	9.73
130	5 ~ 10	40 ~ 45	Africa	9.7	25.09
131	30 ~ 35	40 ~ 45	Asia	9.23	12.24
132	5 ~ 10	5 ~ 10	Africa	9.17	11.15
133	0 ~ 5	30 ~ 35	Africa	8.4	13.71
134	30 ~ 35	60 ~ 65	Asia	8.04	19.72
135	40 ~ 45	15 ~ 20	Europe	6.23	9.97
136	-15 ~ -10	-65 ~ -60	Americas	5.96	13.47
137	5 ~ 10	-15 ~ -10	Africa	5.32	6.86
138	5 ~ 10	35 ~ 40	Africa	4.85	13.71
139	25 ~ 30	-80 ~ -75	Americas	4.78	4.78
140	45 ~ 50	10 ~ 15	Europe	4.3	9.97
141	5 ~ 10	25 ~ 30	Africa	4.25	10.27
142	30 ~ 35	30 ~ 35	Asia	4.02	17.76
143	30 ~ 35	35 ~ 40	Asia	4.02	12.24
144	-15 ~ -10	30 ~ 35	Africa	3.17	34.61
145	15 ~ 20	-65 ~ -60	Americas	3.01	22.47
146	-25 ~ -20	-65 ~ -60	Americas	2.98	14.88
147	-20 ~ -15	-65 ~ -60	Americas	2.98	13.47
148	20 ~ 25	15 ~ 20	Africa	2.9	13.93

149	-5 ~ 0	30 ~ 35	Africa	2.69	16.08
150	-25 ~ -20	25 ~ 30	Africa	2.52	9.14
151	10 ~ 15	0 ~ 5	Africa	2.16	9.17
152	15 ~ 20	5 ~ 10	Africa	2.16	9.52
153	40 ~ 45	20 ~ 25	Europe	1.75	8.58

Table A2: Summary of integrated data for high-risk grids.

Grid	Data source	Number	Resolution (m)	Size (px)	Format
1	RAMP	3,955	0.27	256 × 256	TIF
2	DigitalGlobe	18,569	0.31	256 × 256	TIF
3	Supplement	9,853	0.30	256 × 256	TIF
4	DigitalGlobe	634,795	0.33 ~ 0.53	256 × 256	TIF
5	DigitalGlobe	82,670	0.31	256 × 256	TIF
6	DigitalGlobe	365,809	0.31 ~ 0.49	256 × 256	TIF
7	Supplement	9,982	0.30	256 × 256	TIF
8	DigitalGlobe	58,518	0.34 ~ 0.49	256 × 256	TIF
9	DigitalGlobe	645,722	0.31	256 × 256	TIF
10	DigitalGlobe	244,489	0.46 ~ 0.51	256 × 256	TIF
11	RAMP + DigitalGlobe	1,894,732	0.27 ~ 0.54	256 × 256	TIF
12	DigitalGlobe	167,606	0.43 ~ 0.50	256 × 256	TIF
13	RAMP + DigitalGlobe	1,403,704	0.29 ~ 0.53	256 × 256	TIF
14	DigitalGlobe	2,042,690	0.31 ~ 0.53	256 × 256	TIF

Data availability

The 3H Dataset generated during the current study is scheduled for open-access publication on the Zenodo platform. The dataset analysed during the current study is available in the [EM-DAT] repository, [<https://www.emdat.be/>]. The datasets used or analysed during the current study are available from the corresponding author on reasonable request.

Author contribution

E.Z. prepared the figures and wrote the manuscript. Q.K. prepared the figures and revised the final manuscript. All authors reviewed the manuscript.

Competing interests

The authors declare that they have no conflict of interest.

References

- Baranowski, D. B., Flatau, M. K., Flatau, P. J., et al.: Social-media and newspaper reports reveal large-scale meteorological drivers of floods on Sumatra, *Nature communications*, 11(1), 2503, 2020, <https://doi.org/10.1038/s41467-020-16171-2>.
- Berlemann, M. and Wenzel, D.: Hurricanes, economic growth and transmission channels: Empirical evidence for countries on differing levels of development, *World Development*, 105, 231-247, <https://doi.org/10.1016/j.worlddev.2017.12.020>, 2018.

480 Birkmann, J.: Risk and vulnerability indicators at different scales: Applicability, usefulness and policy implications, *Environmental hazards*, 7, 20-31, <https://doi.org/10.1016/j.envhaz.2007.04.002>, 2007.

Ceferino, L., Kiremidjian, A., and Deierlein, G.: Probabilistic model for regional multiseverity casualty estimation due to building damage following an earthquake, *ASCE-ASME Journal of Risk and Uncertainty in Engineering Systems, Part A: Civil Engineering*, 4, 04018023, <https://doi.org/10.1061/AJRUA6.0000972>, 2018a.

485 Ceferino, L., Kiremidjian, A., and Deierlein, G.: Regional multiseverity casualty estimation due to building damage following a Mw 8.8 earthquake scenario in Lima, Peru, *Earthquake Spectra*, 34, 1739-1761, <https://doi.org/10.1193/080617EQS154M>, 2018b.

Ceferino, L., Merino, Y., Pizarro, S., et al.: Placing engineering in the earthquake response and the survival chain, *Nature Communications*, 15, 4298, <https://doi.org/10.1038/s41467-024-48624-3>, 2024.

490 Chamberlain, E. L., Goodbred, S. L., Steckler, M. S., et al.: Cascading hazards of a major Bengal basin earthquake and abrupt avulsion of the Ganges River, *Nature Communications*, 15, 4975, <https://doi.org/10.1038/s41467-024-47786-4>, 2024.

Chen, P., Zhang, J., Zhang, L., et al.: Evaluation of resident evacuations in urban rainstorm waterlogging disasters based on scenario simulation: Daoli district (Harbin, China) as an example, *International journal of environmental research and public health*, 11, 9964-9980, <https://doi.org/10.3390/ijerph111009964>, 2014).

495 Chitondo, L., Chanda, C., and Phiri, E. V.: Ensuring National Food Security in Southern Africa: Challenges and Solutions, *International Journal of Novel Research in Interdisciplinary Studies*, 11, 1-18, <https://doi.org/10.5281/zenodo.10785042>, 2024.

Coronese, M., Lamperti, F., Keller, K., et al.: Evidence for sharp increase in the economic damages of extreme natural disasters, *Proceedings of the National Academy of Sciences*, 116, 21450-21455, <https://doi.org/10.1073/pnas.1907826116>, 2019.

500 Delforge, D., Wathelet, V., Below, R., et al.: EM-DAT: the emergency events database. *International Journal of Disaster Risk Reduction*, 105509, <https://doi.org/10.1016/j.ijdr.2025.105509>, 2025.

Dilley, M.: *Natural disaster hotspots: a global risk analysis*, World Bank Publications, ISBN 0-8213-5930-4, 2005.

Eckstein, D., Künzel, V., and Schäfer, L.: *Global climate risk index 2021*, Germanwatch, ISBN 978-3-943704-84-6, 2021.

505 Elliott, J., Walters, R., and Wright, T.: The role of space-based observation in understanding and responding to active tectonics and earthquakes, *Nature communications*, 7, 13844, <https://doi.org/10.1038/ncomms13844>, 2016.

Feng, J., Li, N., Zhang, Z., et al.: The dual effect of vegetation green-up date and strong wind on the return period of spring dust storms, *Science of the Total Environment*, 592, 729-737, <https://doi.org/10.1016/j.scitotenv.2017.02.028>, 2017.

Formetta, G. and Feyen, L.: Empirical evidence of declining global vulnerability to climate-related hazards, *Global Environmental Change*, 57, 101920, <https://doi.org/10.1016/j.gloenvcha.2019.05.004>, 2019.

510 Frege, I. A., Radtke, K., Kienzl, P., et al.: *World Risk Report 2023 Focus: Diversity*, Bündnis Entwicklung Hilft / IFHV, ISBN 978-3-946785-16-3, 2023.

Gallina, V., Torresan, S., Critto, A., et al.: A review of multi-risk methodologies for natural hazards: Consequences and challenges for a climate change impact assessment, *Journal of environmental management*, 168, 123-132, <https://doi.org/10.1016/j.jenvman.2015.11.011>, 2016.

515 Geiß, C. and Taubenböck, H.: Remote sensing contributing to assess earthquake risk: from a literature review towards a roadmap, *Natural Hazards*, 68, 7-48, <https://doi.org/10.1007/s11069-012-0322-2>, 2012.

Gill, J. C. and Malamud, B. D.: Reviewing and visualizing the interactions of natural hazards, *Reviews of geophysics*, 52, 680-722, <https://doi.org/10.1002/2013RG000445>, 2014.

520 Herold, S. and Sawada, M. C.: A Review of Geospatial Information Technology for Natural Disaster Management in Developing Countries, *International Journal of Applied Geospatial Research*, 3, 24-62, <https://doi.org/10.4018/jagr.2012040103>, 2012.

Hufschmidt, G., Crozier, M., and Glade, T.: Evolution of natural risk: research framework and perspectives, *Natural hazards and earth system sciences*, 5, 375-387, <https://doi.org/10.5194/nhess-5-375-2005>, 2005.

525 Hussain, M. A., Shuai, Z., Moawwez, M. A., et al.: A Review of Spatial Variations of Multiple Natural Hazards and Risk Management Strategies in Pakistan, *Water*, 15(3), 407, <https://doi.org/10.3390/w15030407>, 2023.

- Julia, P. B. and Ferreira, T. M.: From single-to multi-hazard vulnerability and risk in Historic Urban Areas: a literature review, *Natural Hazards*, 108, 93-128, <https://doi.org/10.1007/s11069-021-04734-5>, 2021.
- Koks, E. E., Jongman, B., Husby, T. G., et al.: Combining hazard, exposure and social vulnerability to provide lessons for flood risk management, *Environmental science & policy*, 47, 42-52, <https://doi.org/10.1016/j.envsci.2014.10.013>, 2015.
- Koks, E. E., Rozenberg, J., Zorn, C., et al.: A global multi-hazard risk analysis of road and railway infrastructure assets, *Nature communications*, 10, 2677, <https://doi.org/10.1038/s41467-019-10442-3>, 2019.
- Lindersson, S., Brandimarte, L., Mård, J., et al.: A review of freely accessible global datasets for the study of floods, droughts and their interactions with human societies, *Wiley Interdisciplinary Reviews: Water*, 7, e1424, <https://doi.org/10.1002/wat2.1424>, 2020.
- Little, A. S., Priestley, M. D., and Catto, J. L.: Future increased risk from extratropical windstorms in northern Europe, *Nature Communications*, 14, 4434, <https://doi.org/10.1038/s41467-023-40102-6>, 2023.
- Manfré, L. A., Hirata, E., Silva, J. B., et al.: An Analysis of Geospatial Technologies for Risk and Natural Disaster Management, *ISPRS International Journal of Geo-Information*, 1, 166-185, <https://doi.org/10.3390/ijgi1020166>, 2012.
- Marin, G., Modica, M., Paleari, S., et al.: Assessing disaster risk by integrating natural and socio-economic dimensions: A decision-support tool, *Socio-Economic Planning Sciences*, 77, <https://doi.org/10.1016/j.seps.2021.101032>, 2021.
- Marin-Ferrer, M., Vernaccini, L., and Poljansek, K.: Index for Risk Management INFORM Concept and Methodology Report - Version 2017, European Union, <https://doi.org/10.2760/094023>, 2017.
- Ming, X., Xu, W., Li, Y., et al.: Quantitative multi-hazard risk assessment with vulnerability surface and hazard joint return period, *Stochastic environmental research and risk assessment*, 29, 35-44, <https://doi.org/10.1007/s00477-014-0935-y>, 2015.
- Mokhtari, M., Faridi, P., Masoodi, M., et al.: Perspective Chapter: A Global View of Natural Hazards Related Disasters, In: *Natural Hazards-New Insights*, IntechOpen, <https://doi.org/10.5772/intechopen.111582>, 2023.
- Mucke, P., Radtke, K., Birkmann, J., et al.: World Risk Report 2011 Focus: Governance and civil society, *Bündnis Entwicklung Hilft*, ISBN 978-3-9814495-1-8, 2011.
- Mucke, P., Radtke, K., Kirch, L., et al.: World Risk Report 2022 Focus: Digitalization, *Bündnis Entwicklung Hilft / IFHV*, ISBN 978-3-946785-14-9, 2022.
- Newman, R., and Noy, I.: The global costs of extreme weather that are attributable to climate change, *Nature Communications*, 14, 6103, <https://doi.org/10.1038/s41467-023-41888-1>, 2023.
- Nohrstedt, D., Hileman, J., Mazzoleni, M., et al.: Exploring disaster impacts on adaptation actions in 549 cities worldwide, *Nature communications*, 13, 3360, <https://doi.org/10.1038/s41467-022-31059-z>, 2022.
- Paprotny, D., Sebastian, A., Morales-Nápoles, O., et al.: Trends in flood losses in Europe over the past 150 years, *Nature communications*, 9, 1985, <https://doi.org/10.1038/s41467-018-04253-1>, 2018.
- Peduzzi, P., Dao, H., Herold, C., et al.: Assessing global exposure and vulnerability towards natural hazards: the Disaster Risk Index, *Natural hazards and earth system sciences*, 9, 1149-1159, <https://doi.org/10.5194/nhess-9-1149-2009>, 2009.
- Peduzzi, P., Chatenoux, B., Dao, H., et al.: Global trends in tropical cyclone risk, *Nature climate change*, 2, 289-294, <https://doi.org/10.1038/nclimate1410>, 2012.
- Pittore, M., Wieland, M., and Fleming, K.: Perspectives on global dynamic exposure modelling for geo-risk assessment, *Natural Hazards*, 86, 7-30, <https://doi.org/10.1007/s11069-016-2437-3>, 2017.
- Rathje, E. M. and Adams, B. J.: The role of remote sensing in earthquake science and engineering: Opportunities and challenges, *Earthquake Spectra*, 24, 471-492, <https://doi.org/10.1193/1.2923922>, 2008.
- Rentschler, J., Salhab, M., and Jafino, B. A.: Flood exposure and poverty in 188 countries, *Nature communications*, 13, 3527, <https://doi.org/10.1038/s41467-022-30727-4>, 2022.
- Ridder, N. N., Pitman, A. J., Westra, S., et al.: Global hotspots for the occurrence of compound events, *Nature communications*, 11, 5956, <https://doi.org/10.1038/s41467-020-19639-3>, 2020.
- Rosvold, E. L. and Buhaug, H.: GDIS, a global dataset of geocoded disaster locations, *Scientific data*, 8, 61, <https://doi.org/10.1038/s41597-021-00846-6>, 2021.
- Shi, P. and Kaspersen, R.: *World atlas of natural disaster risk*, Springer, ISBN 978-3-662-45429-9, 2015.

575 Shi, P., Yang, X., Fang, J., et al.: Mapping and ranking global mortality, affected population and GDP loss risks for multiple climatic hazards, *Journal of Geographical Sciences*, 26, 878-888, <https://doi.org/10.1007/s11442-016-1304-1>, 2016.

Smith, A., Bates, P. D., Wing, O., et al.: New estimates of flood exposure in developing countries using high-resolution population data, *Nature communications*, 10, 1814, <https://doi.org/10.1038/s41467-019-09282-y>, 2019.

580 Taghizadeh-Hesary, F., Sarker, T., Yoshino, N., et al.: Quality infrastructure and natural disaster resiliency: A panel analysis of Asia and the Pacific, *Economic Analysis and Policy*, 69, 394-406, <https://doi.org/10.1016/j.eap.2020.12.021>, 2021.

Tronin, A. A.: Satellite remote sensing in seismology. A review, *Remote Sensing*, 2, 124-150, <https://doi.org/10.3390/rs2010124>, 2009.

United Nations Development Programme (UNDP), Bureau for Crisis Prevention: Reducing disaster risk: a challenge for development-a global report, UNDP, ISBN 92-1-126160-0, 2004.

585 Wang, L., Yu, J. Y., and Paek, H.: Enhanced biennial variability in the Pacific due to Atlantic capacitor effect, *Nature communications*, 8, 14887, <https://doi.org/10.1038/ncomms14887>, 2017.

Ward, P. J., Blauhut, V., Bloemendaal, N., et al.: Review article: Natural hazard risk assessments at the global scale, *Natural Hazards and Earth System Sciences*, 20, 1069-1096, <https://doi.org/10.5194/nhess-20-1069-2020>, 2020.

Welle, T. and Birkmann, J.: The world risk index - an approach to assess risk and vulnerability on a global scale, *Journal of*
590 *Extreme Events*, 2, 1550003, <https://doi.org/10.1142/S2345737615500037>, 2015.

Wen, J., Wan, C., Ye, Q., et al.: Disaster Risk Reduction, Climate Change Adaptation and Their Linkages with Sustainable Development over the Past 30 Years: A Review, *International Journal of Disaster Risk Science*, 14, 1-13, <https://doi.org/10.1007/s13753-023-00472-3>, 2023.

595 Yarveysi, F., Alipour, A., Moftakhari, H., et al.: Block-level vulnerability assessment reveals disproportionate impacts of natural hazards across the conterminous United States, *Nature Communications*, 14, 4222, <https://doi.org/10.1038/s41467-023-39853-z>, 2023.