

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

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Abstract. This study introduces an Accumulated Risk Index (ARI) to map recent global multi-disaster hotspots, leveraging Emergency Events Database (EM-DAT) records from 2013 to 2023. By aggregating World Risk Index (WRI) values for major disaster events within $5^{\circ} \times 5^{\circ}$ latitude-longitude grids, the ARI couples recent hazard occurrences with country-level contextual risk conditions. Results show that 153 grids (5.9% of the global total) have non-zero ARI values, predominantly concentrated across South and Southeast Asia and along the Himalayan belt. Compared to a spatially equivalent WRI, the ARI captures sharper contrasts among neighbouring grids, illuminating the accumulated disaster burden at both transboundary and subnational scales. To facilitate ongoing research in these critical zones, this study additionally presents the 3H Dataset, a standardized compilation of sub-metre remote sensing imagery derived from existing open sources and supplementary acquisitions. This unified dataset offers a complementary resource to support finer-scale, observation-based analyses in high-risk, data-scarce developing regions.

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 accumulated 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 assessment frameworks broadly fall into three methodological paradigms. Indicator-based approaches (e.g., WRI and INFORM) emphasize exposure, vulnerability, and coping-capacity conditions through composite indicators and are therefore effective for portraying relatively stable structural risk patterns. Statistical or event-based approaches (e.g., DRI and Natural Disaster Hotspots) rely more directly

on historical disaster outcomes, such as mortality and economic loss, and are therefore more sensitive to realized impacts. Hybrid approaches (e.g., TRI and MhRI) attempt to combine historical disaster records with broader socio-economic context. These paradigms are complementary rather than mutually exclusive, but they are not equally suitable for all analytical purposes. For the specific objective of this study, identifying where recent major multi-disaster shocks have accumulated at a globally comparable yet spatially differentiated scale, several limitations remain noteworthy.

First, in terms of data timeliness, many existing frameworks are designed to characterize long-term or slowly changing risk trends. Even with regular updates, they may not respond strongly to the concentration of major disaster shocks within a relatively short period, such as the most recent decade. Second, in terms of assessment unit, country-based frameworks facilitate the integration of socio-economic indicators, but they are often too coarse to represent subnational heterogeneity or transboundary disaster corridors, limiting their compatibility with subsequent remote-sensing-based analysis (Shi and Kasperson, 2015; Dilley, 2005; Paprotny et al., 2018; Mucke et al., 2011). Third, in terms of hazard representation, some frameworks focus on a limited set of natural hazards or mix natural and human-induced hazards, which complicates direct comparison in a unified multi-hazard setting. Fourth, in terms of impact indicators, the choice of unified parameters varies widely across studies, from mortality-centred indicators to broader social and economic composites, and each choice involves a trade-off between comparability, interpretability, and multidimensional completeness (Yarveysi et al., 2023; Dilley, 2005; UNDP, 2004; Marin et al., 2021; Frege et al., 2023; Mucke et al., 2022). These considerations suggest that existing frameworks provide important reference points, but they may not fully capture the recent accumulated effects of major disaster events at subnational and transboundary scales.

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 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). Consequently, while remote sensing is invaluable for fine-scale disaster analysis, its direct and uniform deployment within a global risk-assessment framework remains difficult. This practical constraint further motivates the need for an intermediate spatial screening strategy to identify priority areas for subsequent Earth observation analysis.

1.2 Motivation and Objectives

Despite substantial progress in existing risk indices, capturing recent and spatially concentrated disaster impacts at a globally comparable scale remains challenging. First, long-term averages of hazard occurrence and socio-economic indicators may obscure the accumulated impacts of recurrent disaster events observed in the most recent decade. When major events cluster within a relatively short period, their compounded effects may place repeated pressure on local coping capacity and recovery processes, particularly in developing countries (Ridder et al., 2020; Rentschler et al., 2022; Frege et al., 2023). Capturing these near-term accumulated effects therefore requires a complementary 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 subnational or transboundary hazard clusters. Natural hazards follow geophysical processes rather than political borders, and their spatial footprint often 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. In particular, a more spatially explicit framework is needed to better capture cross-border corridors, within-country heterogeneity, and localized accumulated disaster pressure.

Accordingly, this study investigates whether a grid-based accumulation framework, coupling recent major disaster events with country-level contextual risk information, can improve the spatial differentiation of global multi-disaster hotspots beyond conventional national indices. Motivated by this objective, this study introduces the ARI, a global multi-disaster risk assessment index designed to specifically capture the accumulated effects of major disaster events from 2013 to 2023. 85 The index employs $5^{\circ}\times 5^{\circ}$ latitude-longitude grids as its basic assessment unit and incorporates WRI as a contextual weighting coefficient. The proposed ARI aims to provide a 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 90 practitioners and humanitarian organizations, ARI provides a spatially explicit indicator of recent accumulated disaster activity that can guide early recovery efforts and international assistance coordination. 3) For researchers, ARI offers a 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 95 supplements existing sub-metre visible-spectrum remote sensing imagery for ARI-identified high-risk grids, and publishes them as an open-source dataset after standardization. Within the present framework, the ARI dictates spatial prioritization, while the resulting 3H Dataset provides a foundational resource for potential fine-scale applications, including building damage detection, exposure mapping, and post-disaster recovery monitoring.

Table 1: Representative frameworks for 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 the 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 accumulated 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). Accordingly, the present framework mainly targets sudden-onset hazard processes for which major event accumulation can be more directly represented within EM-DAT records and more plausibly connected to Earth observation applications. 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 does not imply that mortality fully captures disaster risk or impact. Rather, it is adopted here as a pragmatic and comparatively more consistent proxy for recent high-impact events under global data constraints. Population-based indicators in EM-DAT, such as “No. Affected” and “No. Homeless”, are often influenced by differences in national definitions and estimation practices, which depend heavily on other metrics or overall event assessments (UNDP, 2004; Newman and Noy, 2023; Peduzzi et al., 2009). Similarly, economic indicators such as “Total Damage” are strongly shaped by uneven valuation systems, reporting capacity, and development levels across countries (UNDP, 2004; Peduzzi et al., 2009). Consequently, mortality is used in this study as an operational screening variable with relatively stronger cross-country comparability.

Similarly, the threshold of ≥ 50 fatalities represents a pragmatic methodological compromise rather than an absolute theoretical cut-off. A lower threshold would incorporate numerous small-scale events, thereby exacerbating sensitivity to uneven reporting biases, whereas a much higher threshold would severely restrict the sample size required for robust global spatial comparisons. Therefore, this study employs the ≥ 50 criterion to retain a sufficient number of events for meaningful grid-based accumulation analysis, while selectively emphasizing disasters that cause major socio-economic disruption. The sensitivity of this choice is further evaluated in Section 3.3.2. Inherently, this also means that the present framework prioritizes mortality-screened major events and does not fully capture economic-loss-dominated disasters, indirect cascading impacts, or slow-onset hazard processes.

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.

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 the final analysis, as there are no records of major events with at least 50 fatalities during the study period. This exclusion is fundamentally data-driven within the present framework, rather than an a priori methodological deletion. At the same time, this outcome may bias the final event composition toward hazard subtypes prone to generating short-term, high-mortality impacts.

2.2 Spatial standardization

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. In addition, certain disaster events, notably floods and storms, may affect broad or spatially discontinuous areas, which makes direct spatial comparisons inherently difficult when only textual location descriptions are available.

To support consistent grid-based aggregation, this study employs a systematic approach to location data processing, converting each major disaster event into a single representative coordinate. When precise latitude-longitude coordinates are already provided within EM-DAT, they are retained directly. For events recorded only through textual descriptions, all reported affected locations are first reviewed, and one representative site is then selected according to two priority principles: proximity to the geographic center of the overall affected area, and spatial coincidence with the most severe disaster impacts. The latitude-longitude coordinates of the selected site are subsequently derived from available administrative boundary data, providing an approximate but standardized basis for disaster location identification.

For events spanning multiple administrative units, the assignment is strictly limited to one representative coordinate to

ensure that each event is allocated to a single grid cell, thereby avoiding double-counting across adjacent grids. This point-based standardization is intended to enable uniform global allocation for ARI calculation, rather than to reconstruct the detailed spatial footprint of each disaster event. Therefore, inherent spatial simplifications and uncertainties are unavoidable, particularly for geographically extensive events, and this limitation is further discussed in Section 5. 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.

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 expression used here to illustrate 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:

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

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 accumulated effects of recent major disaster events when conducting risk assessments.

In the present study, WRI is adopted as a reference index because it provides a well-established and annually updated country-level representation of exposure and vulnerability conditions. Its comprehensive indicator system and multi-hazard orientation make it suitable for contextualizing disaster events across regions with different socio-economic backgrounds (Frege et al., 2023; Mucke et al., 2022). However, WRI is not designed to capture the short-term spatial accumulation of recent disaster shocks at subnational or transboundary scales. Methodologically, it is constrained by its country-level assessment unit, and its relatively broad statistics for accumulated impacts, including “Internally displaced persons due to natural disasters” and “Population affected by disasters in the last 5 years” from a perspective of vulnerable groups, which may compromise data reliability as discussed in Section 2.1. Therefore, while WRI provides valuable structural context, it remains inherently insufficient as a standalone metric for identifying recent grid-level clustering of major disaster impacts.

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, encapsulating the broader exposure-vulnerability setting in which disaster events occur. The proposed ARI builds on this reference framework by combining recent major disaster events with national WRI values at the grid scale. Conceptually, ARI integrates two components: 1) the number of major disaster events assigned to each grid cell from 2013 to 2023, based on the event filtering strategy in Section 2.1 and the spatial standardization procedure in Section 2.2; and 2) the WRI value of the country 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 major disaster shocks in contexts with varying underlying risk conditions. The index is defined as:

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

where ARI_j is the ARI of grid cell j , n_j is the number of major disaster events assigned to grid cell j from 2013 to 2023, i indexes the events occurring in that grid cell, $c(i)$ denotes the country associated with the i -th event according to the EM-DAT record, and $WRI_{c(i)}$ is the WRI value of that country. When $n_j = 0$, ARI_j is strictly defined as 0. In this formulation, ARI represents the accumulated sum of country-level WRI weights associated with recent major disaster events occurring within each grid cell, rather than a direct spatial aggregation of WRI itself. ARI should therefore be interpreted as an event-driven, grid-based, context-weighted relative index, rather than a complete physical-statistical representation of disaster risk.

In the current implementation, all major events above the ≥ 50 fatalities threshold contribute equally to ARI, regardless of their exact death toll. This design keeps the interpretation of ARI transparent: once an event satisfies the major-event

criterion defined in Section 2.1, it is counted as one accumulated shock, and differences in background risk are reflected through the associated country-level WRI value. This simplification avoids introducing additional uncertainty from severity weighting and allows a clearer interpretation of ARI as an index of recent accumulated disaster stress rather than a full description of all severity dimensions.

The selection of WRI as the reference framework for ARI is supported by four main considerations: 1) WRI is updated regularly through WRR and remains methodologically current; 2) its indicator system spans social, economic, political, and environmental dimensions, making it a comprehensive country-level contextual index; 3) it adopts a multi-hazard perspective rather than focusing on a single hazard; and 4) its quantitative scoring system facilitates comparison and further computation (Frege et al., 2023; Mucke et al., 2022). In ARI, these advantages are retained while shifting the analytical focus from long-term structural risk to the recent accumulation of major disaster events. Although WRI and the present study do not use exactly the same hazard taxonomy, both concentrate on major natural hazards affecting large populations. Given the aggregate role of WRI and the exploratory purpose of ARI, these differences 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 preserves the link between individual disaster records and their national risk contexts, instead of assigning one single WRI value to the entire grid cell in advance. 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

The statistical computation of ARI depends on the selection of grid cell, which in principle could correspond to different types of spatial assessment units. In this study, however, the objective is to identify recent multi-hazard accumulation patterns at the global scale while retaining a spatial resolution finer than national boundaries. This requires a grid size that is large enough to accommodate the positional uncertainty and broad footprint of some disaster events, but still sufficiently refined to reveal subnational and transboundary clustering.

The choice of spatial unit is therefore a methodological trade-off. If the grid size is excessively large, the main advantage of moving beyond country-level assessment units is weakened, and localized accumulated patterns may be obscured. If the grid size is overly small, two problems become more pronounced. First, 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. Second, the spatial uncertainty and locational error introduced by representative event coordinates, as described in Section 2.2, will be relatively amplified as cell size decreases. 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.

For these reasons, this study adopts a $5^{\circ} \times 5^{\circ}$ latitude-longitude grid as the minimum assessment unit for ARI computation. This resolution is intended to provide a practical balance among global coverage, spatial differentiation, data reliability, and compatibility with remote sensing applications. To examine the sensitivity of this choice, alternative grid sizes of $2.5^{\circ} \times 2.5^{\circ}$ and $10^{\circ} \times 10^{\circ}$ are evaluated 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-metre satellite imagery. Existing open-source data are compiled and supplemented where necessary to form the proposed dataset (Section 4). In this sense, ARI serves as the hotspot-screening mechanism that guides where remote sensing resources are prioritized, while the 3H Dataset provides the geospatial data foundation for subsequent finer-scale studies in those selected high-risk areas. This workflow demonstrates that the remote sensing component is not independent of the risk model, but is developed as an operational extension of it. Specifically, ARI identifies where recent accumulated disaster pressure is concentrated, and the 3H Dataset translates those hotspot results into a standardized imagery resource that can support future applications. Together, these methodological stages constitute an integrated framework linking historical disaster records, contextual risk information, and Earth observation data.

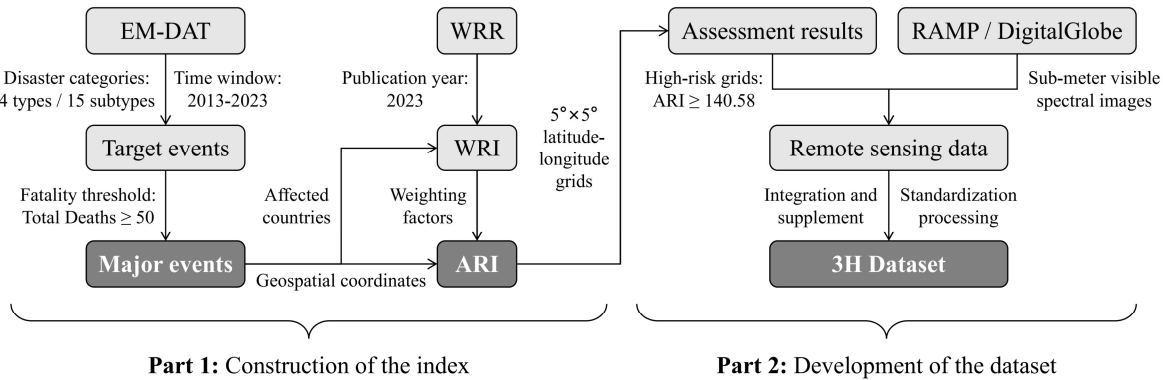


Figure 1: Methodology workflow diagram.

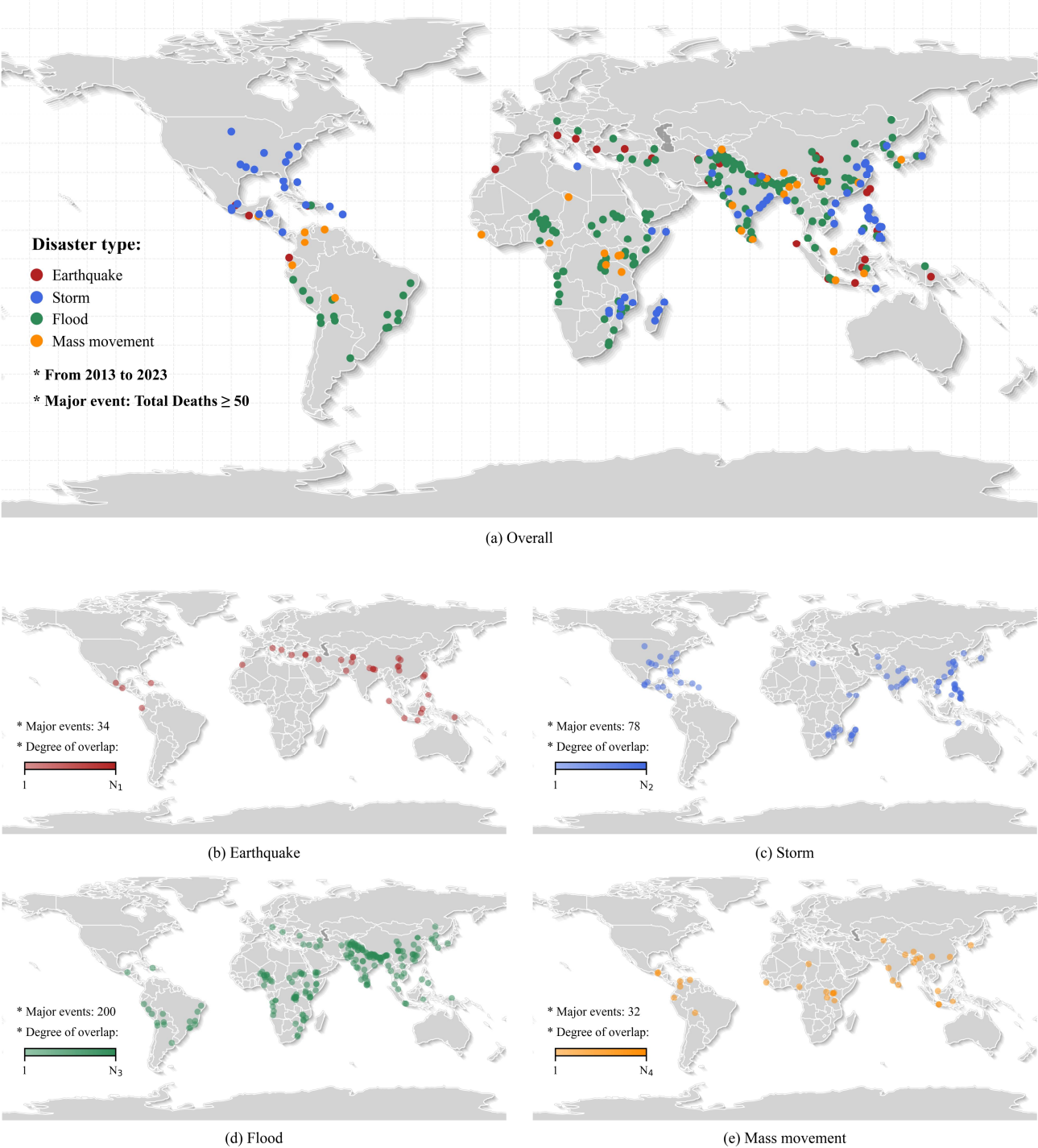
3 Results

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. These percentages describe the hazard composition of the selected major-event sample under the present framework. The distribution reveals that floods dominate this mortality-screened event set, followed by storms, whereas earthquakes and mass movements account for smaller but still non-negligible proportions.

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. In panels (b)-(e), semi-transparent event points are superposed to indicate local clustering intensity. The notations N₁-N₄ represent the maximum spatial overlap of

310 plotted points in the corresponding subpanels, and the overlap degree is directly derived from this visual superposition as an approximate proxy for local event concentration rather than a formal geospatial statistic.



N_1 - N_4 : 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 selected major disaster events. (a) Global overview. Panels (b)-(e) visualize local event clustering using semi-transparent points. The notations N_1 - N_4 denote the peak point superposition density, which serves as an approximate indicator of local disaster concentration within respective subpanels.

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

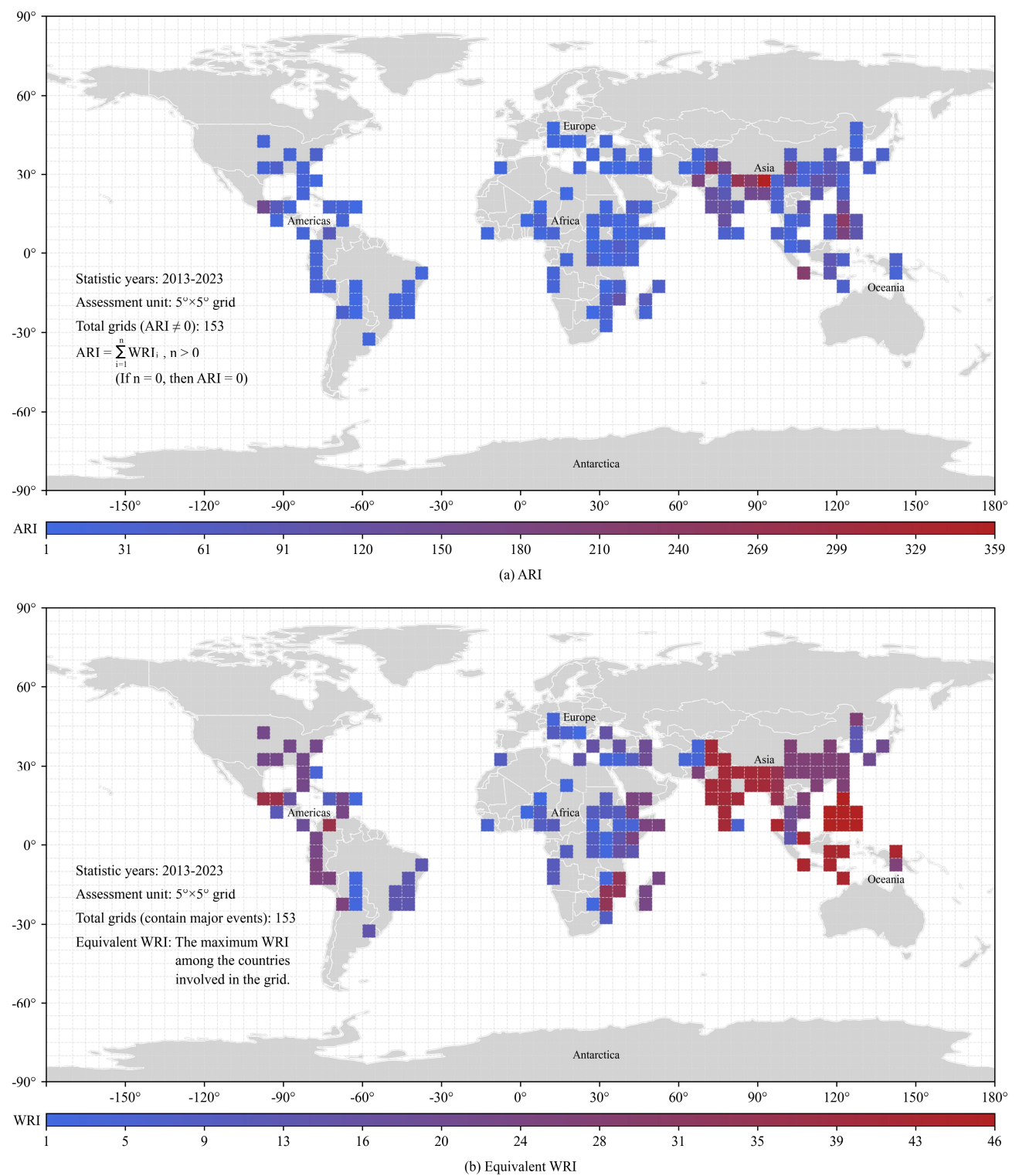


Figure 3: Global distributions of (a) ARI and (b) Equivalent WRI in 5°×5° latitude-longitude grids. The two panels use analogous colour progression but different numerical ranges.

Using the 5°×5° 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 accumulated impacts of major disasters during 2013-2023. Overall, the global distribution of ARI is strongly uneven, indicating that the accumulated impacts of recent major disaster events are concentrated in a relatively limited set of hotspot regions.

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. Although Figure 3(a) and Figure 3(b) use analogous colour progression, they retain different numerical ranges because ARI and Equivalent WRI serve different analytical roles. ARI is a grid-based index of recent event accumulation, whereas Equivalent WRI is a grid-level reference indicator derived from country-level background risk. Therefore, the comparison is intended to emphasize differences in spatial pattern and relative contrast rather than direct equivalence of colour values between the two maps. From this perspective, ARI reveals sharper subnational and transboundary differentiation than Equivalent WRI, especially in areas affected by repeated recent disaster shocks.

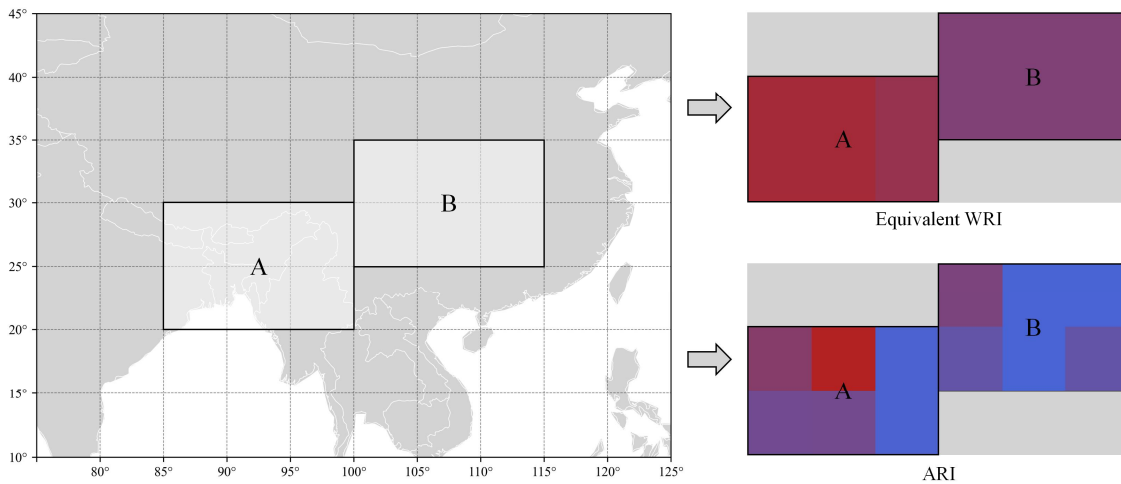


Figure 4: Local zoom-in comparison of ARI and Equivalent WRI in 5°×5° latitude-longitude grids.

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 progression as in Figure 3.

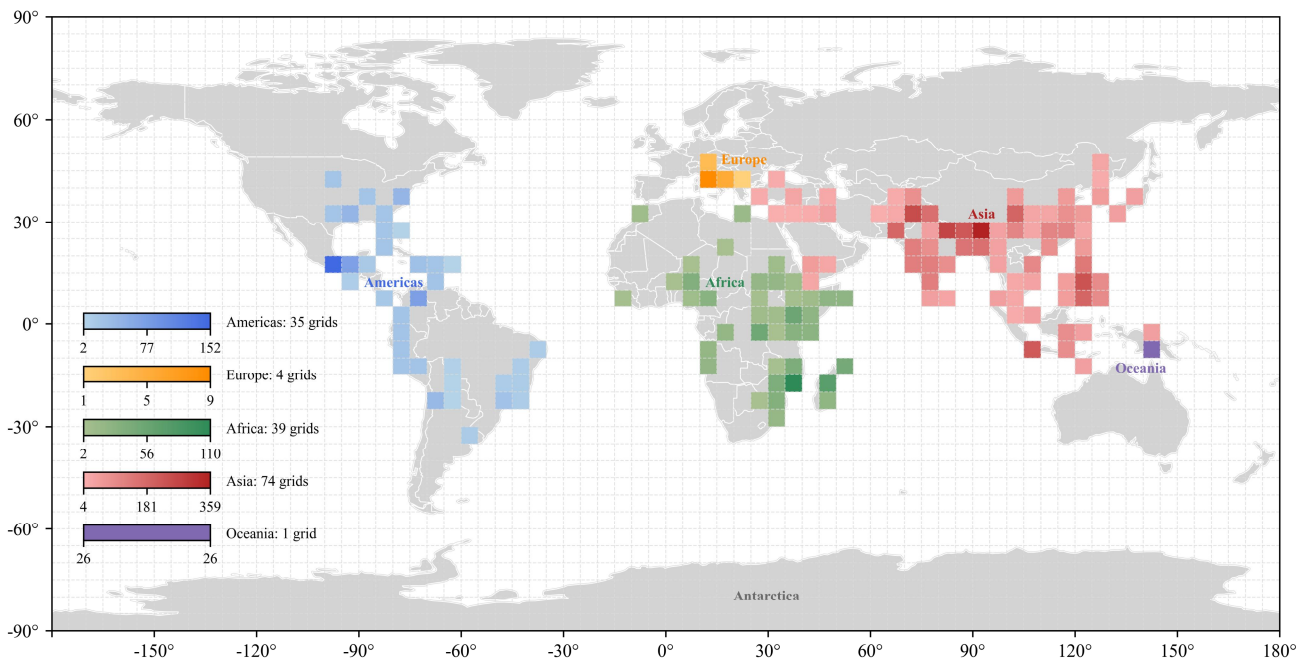
Two contrasting situations are illustrated. In Window A, which spans multiple countries, Equivalent WRI mainly reflects country-level background differences, whereas ARI further differentiates neighbouring 5°×5° cells according to the spatial concentration of recent major events within the same transboundary 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 subnational hotspots associated with recent event accumulation. Taken together, Figure 4 makes the contrast in Figure 3 more explicit: incorporating near-term event accumulation does not simply reproduce the country-based background pattern, but adds spatial discrimination along transboundary hazard corridors and within large countries where subnational variability is important.

To further examine regional variability, ARI results are grouped by continental plates (Americas, Europe, Africa, Asia and

365 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.

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

375



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

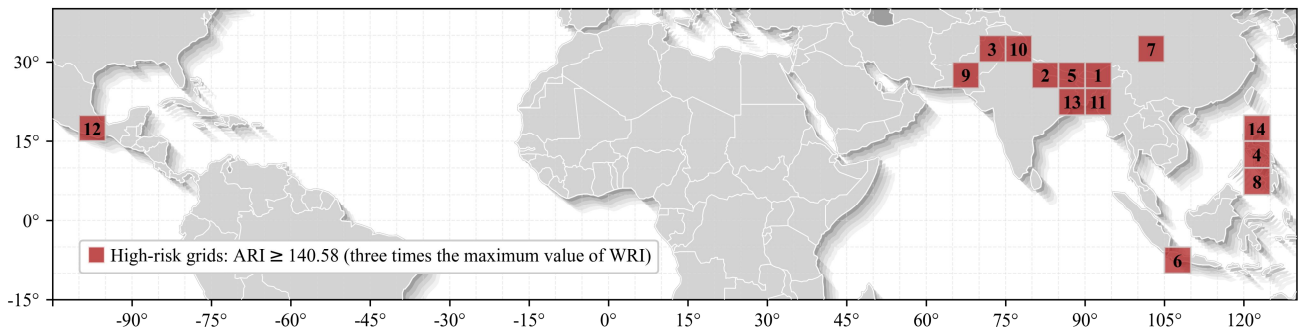


Figure 6: Spatial distribution of high-risk grids.

3.3 External plausibility assessment and robustness checks

Given that ARI is a newly proposed index, it is important to examine both whether its hotspot pattern shows meaningful external plausibility and whether its main spatial features remain stable under reasonable methodological variation.

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Accordingly, this section consists of two complementary parts. First, an out-of-sample comparison is conducted using major disaster events that occurred in Asia during 2024, after the study period used to construct ARI, which is intended as an external plausibility assessment. Second, robustness checks are performed to evaluate the sensitivity of ARI to the fatality threshold used to define major disaster events and to the spatial resolution of the latitude-longitude grid.

3.3.1 Out-of-sample plausibility assessment

Because the ARI in this study is calculated from disaster events during 2013-2023, major disaster events that occurred in 2024 provide a natural post-period reference set for evaluating whether later major events tend to occur in areas already identified as ARI hotspots. To keep this additional analysis focused and tractable while remaining representative, the comparison is conducted for Asia, which is also the region where ARI exhibits the strongest and most continuous hotspot pattern in Figure 3.

Following the same event-selection logic used in the main analysis, major disaster events in Asia during 2024 are extracted from EM-DAT using the criterion of Total Deaths ≥ 50 . Each event is then matched to its corresponding $5^\circ \times 5^\circ$ grid cell. For each such cell, the ARI ranking derived from the 2013-2023 analysis is recorded and compared with the corresponding country-level WRI ranking. The resulting event list is summarized in Table 4, and the spatial correspondence between the 2024 events and the Asia ARI map is shown in Figure 7.

Table 4: Major disaster events in Asia during 2024 from EM-DAT and their corresponding ARI and WRI rankings.

Disaster subgroup	Disaster type	Disaster subtype	Country	Total deaths	ARI ranking	WRI ranking
Geophysical	Earthquake	Ground movement	Japan	699	54	24
Meteorological	Storm	Tropical cyclone	Myanmar	460	11	6
Hydrological	Mass movement (wet)	Landslide (wet)	India	378	15	3
Hydrological	Flood	Flood (General)	Pakistan	368	3	11
Hydrological	Flood	Flood (General)	Afghanistan	357	32	98
Meteorological	Storm	Tropical cyclone	Viet Nam	345	-	15
Hydrological	Flood	Flood (General)	Nepal	268	2	138
Hydrological	Flood	Flood (General)	Yemen	240	43	15
Meteorological	Storm	Tropical cyclone	Philippines	181	4	1
Hydrological	Flood	Flash flood	Afghanistan	150	106	98
Meteorological	Storm	Tropical cyclone	China	129	20	10
Hydrological	Mass movement (wet)	Landslide (wet)	Philippines	128	24	1
Hydrological	Flood	Flood (General)	India	125	2	3
Hydrological	Flood	Flood (General)	Indonesia	87	-	2
Hydrological	Flood	Flood (General)	China	77	20	10
Hydrological	Flood	Flash flood	Bangladesh	71	11	9
Hydrological	Flood	Flood (General)	China	65	20	10
Hydrological	Mass movement (wet)	Landslide (wet)	Nepal	62	2	138
Hydrological	Flood	Flood (General)	Yemen	62	43	15
Hydrological	Mass movement (wet)	Landslide (wet)	Indonesia	59	6	2
Hydrological	Flood	Flash flood	Afghanistan	58	3	98
Meteorological	Storm	Tropical cyclone	Philippines	53	4	1
Meteorological	Storm	Tropical cyclone	India	51	1	3

The comparison shows that most major disaster events in Asia during 2024 occurred in grid cells with relatively high ARI rankings, which supports the interpretation that ARI identifies locations subject to meaningful recent accumulated disaster pressure. Figure 7 further illustrates that many of the post-period events are spatially concentrated within or near the

principal ARI hotspot belts identified from the 2013-2023 event set. This assessment also suggests that ARI can reveal spatial structures that are not readily apparent from country-level WRI alone. For example, some 2024 events in Nepal occurred in a grid cell with a very high ARI ranking, despite Nepal’s comparatively modest country-level WRI ranking. This reflects the fact that the corresponding grid accumulates major events from both Nepal and neighboring India, thereby capturing a transboundary accumulated-impact corridor that is less visible in a country-based index.

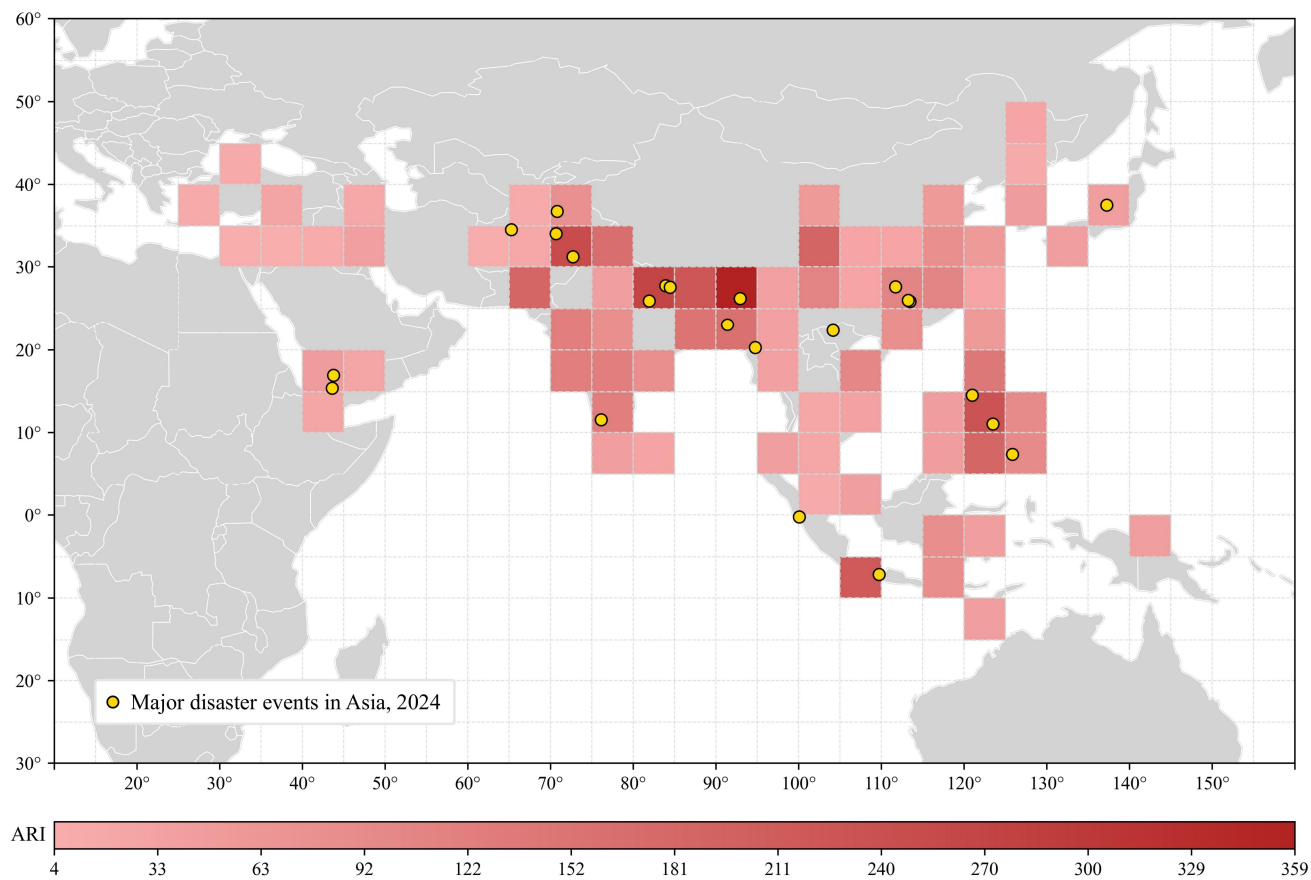


Figure 7: Asia ARI in 5°x5° latitude-longitude grids and major disaster events in Asia during 2024.

At the same time, this comparison also clarifies the conceptual boundary of ARI. Only two of the 2024 major events occurred in grid cells with no prior ARI value, such as the cases shown with “-” in Table 4. These cases do not necessarily contradict the index logic. Instead, they indicate that ARI is not intended as a universal predictor of all future major disasters, but as a backward-looking indicator of recent accumulated shock pressure. If a grid experiences a major event in 2024 but had no qualifying major events during 2013-2023, the absence of a prior ARI signal is consistent with the way ARI is defined. In this sense, accumulated risk and general disaster risk are related but not identical concepts. Therefore, the 2024 Asia comparison should be interpreted as an external plausibility assessment rather than definitive validation in a strict predictive sense. It strengthens confidence that ARI captures meaningful hotspot structures of recent accumulated disaster pressure, while also underscoring the need to interpret the index within its intended temporal and conceptual scope.

3.3.2 Sensitivity to the fatality threshold

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. These values represent a reasonable neighborhood around the baseline setting and are used to evaluate whether moderate threshold variation changes the principal hotspot pattern. For each threshold, the number of major events and the ARI values of grids are recalculated. Table 5 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 5: 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

430 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. These changes affect the absolute magnitude of ARI and
 the number of included events, but they do not fundamentally alter the dominant hotspot geography. In all scenarios, the
 highest-ranking grids remain concentrated 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
 435 those in the baseline configuration, often with only moderate changes in rank. This pattern indicates that the identification
 of the principal high-risk clusters is not strongly dependent on one exact threshold value, even though the event counts and
 ARI magnitudes vary as expected.

3.3.3 Sensitivity to the 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 8 compares the resulting ARI distributions under these alternative 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 indicates that the broad spatial concentration of ARI is not an artifact of the single baseline resolution, but persists across reasonable changes in grid size.

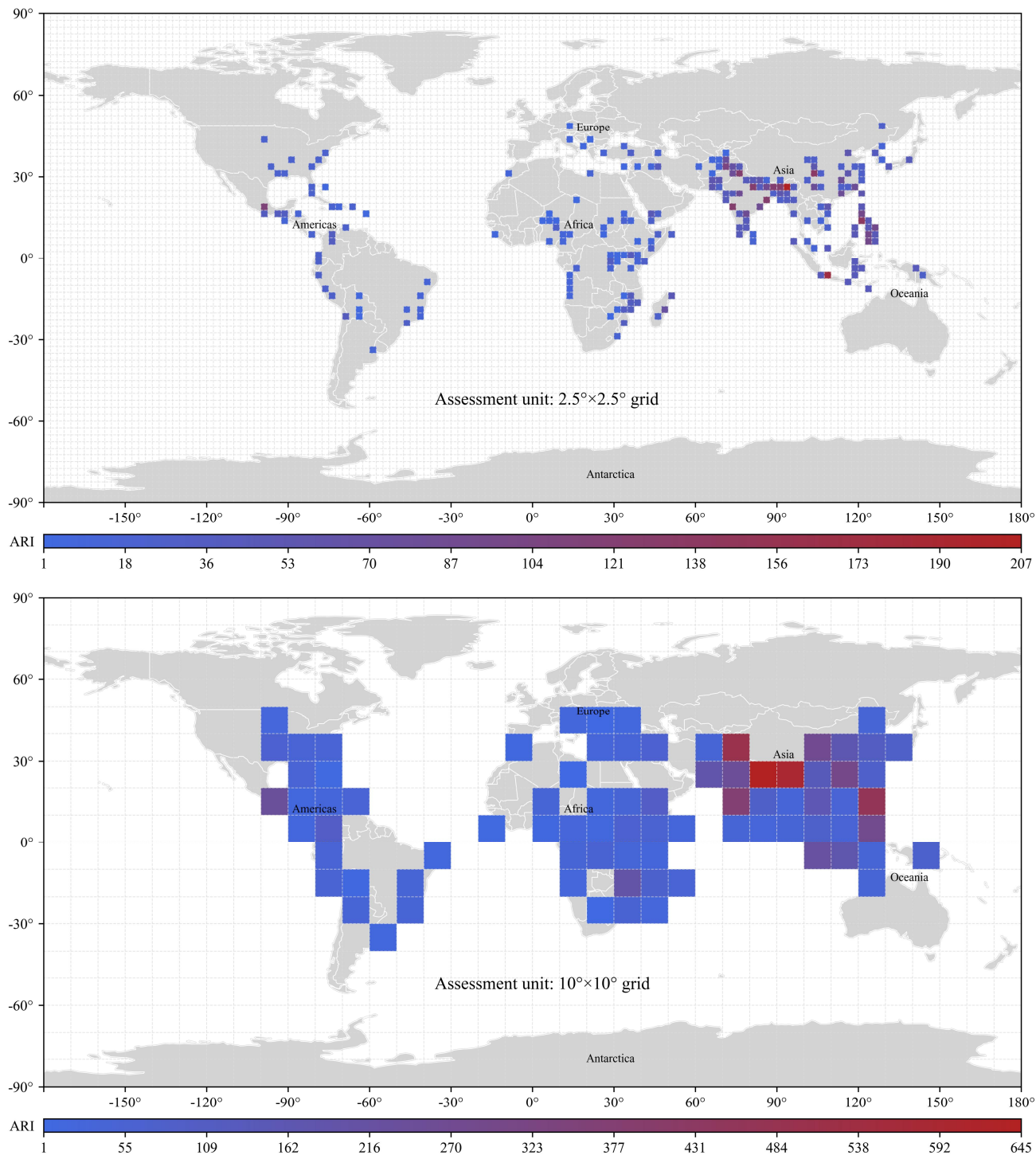


Figure 8: Comparison of ARI results under different spatial grids ($2.5^{\circ}\times 2.5^{\circ}$ and $10^{\circ}\times 10^{\circ}$).

Taken together, the out-of-sample plausibility assessment and the robustness checks indicate that ARI identifies spatially

coherent and comparatively stable hotspot patterns at the global scale. The strongest claim supported by the current evidence is therefore not that ARI has been definitively validated as a complete measure of true disaster risk, but that it shows meaningful external plausibility when compared with the spatial occurrence of subsequent major disaster events and remains robust under reasonable variation in key methodological parameters. These results support the use of ARI as a comparative hotspot-identification framework, while detailed local interpretation should still consider the methodological 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-metre visible-spectrum 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 study, the remote sensing component is developed as a complementary operational extension of the ARI framework. ARI first identifies hotspot grids where recent accumulated disaster pressure is concentrated, and remote sensing data are then compiled and supplemented within those ARI-identified locations. The resulting 3H Dataset is therefore organized at the hotspot-grid level and is intended to support subsequent finer-scale Earth observation and machine-learning studies in these areas. Within the present manuscript, its role is to provide a standardized geospatial data foundation rather than to serve as a direct image-based validation of ARI.

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-spectrum imagery covering these grids. Figure 9 shows the spatial distribution of the available imagery sources associated with the ARI hotspots. 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>).

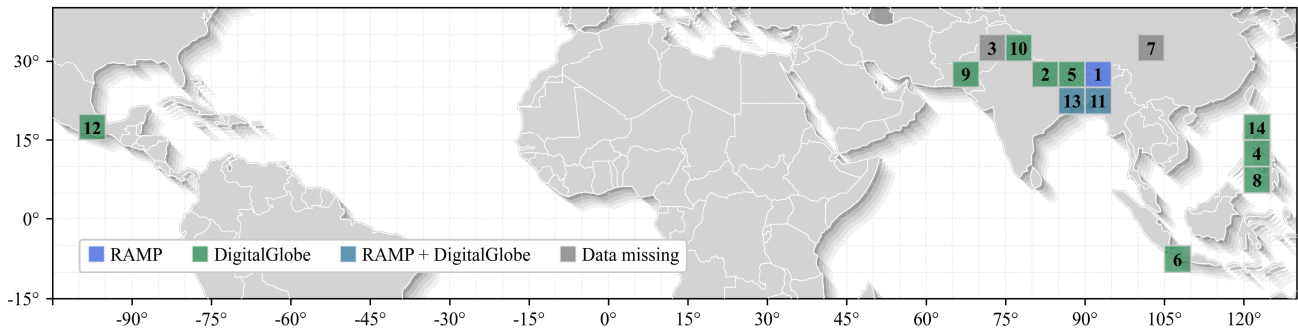


Figure 9: Spatial distribution of existing imagery sources for ARI-identified high-risk grids.

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Using these sources, sub-metre visible-spectrum images were compiled for the set of high-risk grids identified by ARI. Table 6 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. The resulting spatial coverage is not globally balanced. This concentration is produced by two interacting factors: first, ARI hotspots during 2013-2023 are themselves concentrated mainly in South Asia, Southeast Asia, and the Himalayan belt; second, the global availability of open high-resolution imagery is geographically uneven. As a result, the 3H Dataset should be understood as a targeted hotspot-oriented collection rather than a globally balanced remote sensing benchmark.

Table 6: Detailed information of imagery sources for all 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

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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 6) lack suitable open-source imagery. To address these gaps, additional visible-spectrum 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 selected according to the most severe major event within the corresponding hotspot grid, specifically the event with the maximum “Total Deaths” recorded in that cell. This event-centred refinement was applied only to these supplementary acquisitions in data-scarce grids and does not alter the overall hotspot-oriented design of the 3H Dataset. The supplemented images were

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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. The overall process can be summarized as follows: 1) ARI-guided hotspot selection; 2) source imagery collection within the selected grids; 3) visual quality screening of candidate scenes; 4) spatial standardization and tiling; and 5) metadata assignment and final dataset organization.

First, candidate scenes were visually inspected to remove imagery with severe artefacts, substantial cloud, cloud-shadow, or haze contamination that prevented reliable interpretation of built-up targets. In addition, scenes with little or no meaningful built-up content were excluded because they were poorly aligned with the intended downstream applications of the dataset. At the present stage, this screening procedure was based primarily on manual visual inspection rather than a fully automated filtering framework. Second, the retained scenes were spatially standardized and tiled into fixed-size patches of 256×256 pixels. Third, all tiles were stored in TIF format and annotated with the corresponding hotspot-grid identifier and data source so that each standardized unit could be linked back to its originating imagery and ARI-identified grid location. This workflow 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 countries. Figure 10 provides representative examples of the imagery, illustrating the diversity of urban forms, building densities and environmental contexts captured by the dataset.

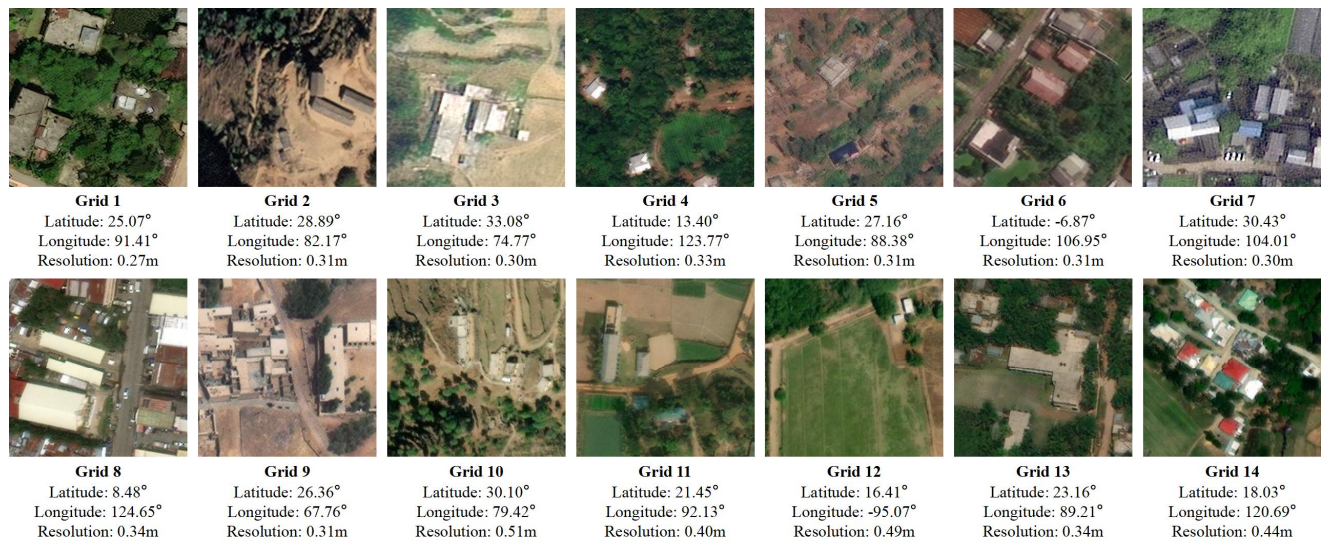


Figure 10: Examples of data in 3H Dataset. Most of the materials are collected and prepared from RAMP and DigitalGlobe, while the remaining data are acquired and produced by the authors.

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 hotspot grids in developing countries and by providing imagery in a standardized format, the 3H Dataset is intended to support future finer-scale studies such as building damage detection, exposure mapping, and post-disaster recovery monitoring. In this way, it complements the macro-scale ARI framework by making high-risk, data-scarce locations more accessible for subsequent Earth observation analysis.

5 Discussion

The central contribution of this study lies in reframing global multi-disaster assessment from a purely structural or country-based perspective toward a spatially explicit view of recent accumulated disaster pressure. Existing global indices such as the WRI remain highly valuable because they provide a broad and systematic representation of exposure and vulnerability conditions at the national scale. However, the results of this study suggest that such structural risk context alone may not fully express where major disaster shocks have clustered most intensely in recent years. In this sense, the ARI does not seek to replace long-term structural risk metrics, but to complement them by emphasizing a dimension that is often muted in country-level frameworks: the short-term accumulation of major disaster events across subnational and transboundary space. This complementary role is most clearly reflected in the sharper hotspot contrasts observed in ARI, particularly along the Himalayan belt, South and Southeast Asia, and other cross-border corridors where repeated high-impact events have occurred within a relatively short period.

From a broader disaster-risk perspective, this distinction is important because resilience deterioration is not only a function of background vulnerability, but also of repeated shock exposure over time. A location may be embedded in a high-vulnerability national context without having experienced concentrated recent shocks, just as a location with only moderate country-level background risk may nonetheless emerge as a hotspot when multiple major events accumulate in close spatial proximity. The comparison between ARI and Equivalent WRI illustrates precisely this point: ARI contributes an additional temporal-spatial layer to global disaster assessment by identifying where recent disaster accumulation may have intensified pressure beyond what long-term structural indices alone would suggest. The added value of the proposed framework therefore lies less in redefining disaster risk in a universal sense than in revealing where recent accumulated impacts may warrant heightened analytical and practical attention.

At the same time, the present results also clarify the evidentiary status of ARI. The analyses in Section 3.3 indicate that the index exhibits meaningful external plausibility and internal robustness, but they do not justify stronger claims than that. The 2024 Asia comparison shows that many post-period major disaster events occurred within or near the principal hotspot belts identified from 2013-2023, which supports the interpretation that ARI captures spatially meaningful structures of recent accumulated disaster pressure. Likewise, the sensitivity tests on fatality threshold and grid resolution show that the main hotspot geography remains broadly stable under reasonable methodological variation. Taken together, these findings strengthen confidence in ARI as a comparative hotspot-identification framework. They do not, however, establish ARI as a definitive or exhaustive measure of disaster risk. This distinction is critical. ARI is best interpreted as a relative indicator of where recent major disaster shocks have accumulated under different country-level risk contexts, not as a complete substitute for structural risk models, nor as a universal predictor of future disasters.

This interpretation also helps place the limitations of the study in a more constructive light. The current framework is necessarily selective. Its mortality-based event filtering improves cross-country comparability and reduces the noise of under-reported small events, but it also privileges short-onset, high-fatality shocks and does not fully capture economic losses, indirect impacts, prolonged disruption, or many slow-onset processes. Similarly, the final hazard composition is shaped by the study period and inclusion rule, which means that the resulting event set should not be mistaken for a hazard-neutral representation of all disaster processes recorded in EM-DAT. At the spatial level, the use of one representative coordinate per event makes global grid-based aggregation feasible, but inevitably compresses the true footprint of geographically extensive hazards such as floods and storms. At the contextual level, ARI depends on the strengths and weaknesses of both EM-DAT and WRI: the former is affected by reporting heterogeneity and imperfect geolocation, while the latter provides only country-level contextual risk information and aggregates diverse indicators with uneven temporal update cycles. These are not minor caveats. They define the scope within which the present results should be read. Yet they also point directly to the specific directions in which accumulated-risk assessment can be improved.

Within those boundaries, the combined ARI-remote sensing framework still offers a meaningful contribution. For

575 policymakers, ARI provides a way to screen for broad regions where repeated high-impact events may have intensified disaster pressure and where preparedness, resilience-building, or capacity support may need to be prioritized. For practitioners and humanitarian actors, the identified hotspot grids can serve as a spatial cue for where finer-scale assessment, field verification, or observation-based monitoring may be most warranted. For researchers, the 3H Dataset extends the ARI framework from hotspot identification to data infrastructure by making sub-metre imagery available in a
580 standardized form for high-risk, data-scarce regions. Importantly, this dataset should be understood in the same spirit as ARI itself: not as a globally balanced benchmark, but as a targeted resource oriented toward empirically identified hotspot zones, especially in developing countries where the gap between disaster exposure and data accessibility remains pronounced.

Seen from this perspective, the broader significance of the study is not only methodological but also infrastructural. ARI
585 provides a macro-scale screening logic for identifying where recent accumulated pressure is concentrated, while the 3H Dataset offers a micro-scale observational basis for examining what those hotspots look like on the ground. The two components therefore operate at different but connected scales. Together, they suggest a possible pathway for linking global disaster statistics, contextual risk conditions, and Earth observation resources in a more operationally coherent way than is commonly achieved in either purely index-based or purely image-based studies.

590 These considerations also make the next steps for future research more concrete. A first priority is to move from the present static formulation toward dynamic or temporally weighted ARI variants, so that more recent shocks, or repeated shocks occurring before recovery is complete, can be represented more realistically. A second priority is to improve event representation itself through finer geocoding, better footprint allocation, and the integration of Earth-observation-derived hazard extents, especially for spatially extensive disasters. A third direction is to enrich the impact basis of the framework
595 by exploring composite severity formulations that combine mortality with other dimensions such as affected population, economic disruption, infrastructure damage, or remotely sensed damage proxies when data quality allows. A fourth direction is to link ARI more explicitly with forward-looking analysis, including projected hazard changes under climate scenarios and evolving socio-economic conditions, so that the current retrospective accumulation logic can be related to possible future risk trajectories. Finally, the ARI-guided 3H Dataset opens an avenue for subsequent machine-learning
600 applications, including building damage detection, exposure mapping, recovery monitoring, and domain adaptation in data-scarce regions. Such finer-scale outputs may, in turn, provide new evidence for further refining and evaluating accumulated-risk indicators.

In summary, the present study suggests that recent disaster accumulation deserves more explicit attention in global risk assessment than it typically receives in long-term country-based frameworks. ARI does not resolve the full complexity of
605 global disaster risk, nor is it intended to do so. Its contribution is more focused: to identify where major disaster shocks have recently clustered under different national risk contexts, and to translate that identification into a spatial framework that can support subsequent observation-based analysis. Under that more disciplined interpretation, the value of ARI lies not in replacing existing indices, but in extending the analytical vocabulary available for understanding how repeated disaster shocks are distributed across space and where their accumulated pressure may be most consequential.

610 **6 Conclusions**

This study proposes the ARI as a grid-based and event-driven framework for examining recent accumulated disaster impacts at the global scale. By combining major disaster events recorded in EM-DAT during 2013-2023 with country-level WRI values, ARI adds explicit sensitivity to the spatial accumulation of recent high-impact shocks across subnational and transboundary space. The results reveal clear hotspot concentration, especially across the Himalayan belt, South Asia, and
615 Southeast Asia, and show that ARI provides stronger spatial differentiation than a country-based reference framework. In

this sense, ARI is not intended to replace long-term structural risk indices, but to complement them by highlighting where recent major disaster shocks have clustered most strongly. The analyses further indicate that ARI shows meaningful external plausibility and internal robustness as a comparative hotspot-identification framework, while remaining a relative indicator rather than a complete measure of absolute disaster risk. Building on the ARI-identified hotspot grids, this study also develops the 3H Dataset, which contains more than 7.5 million standardized sub-metre remote sensing image tiles across 14 high-risk grids in 10 developing countries. Together, ARI and the 3H Dataset provide a connected basis for linking global disaster statistics, contextual risk information, and Earth observation resources, thereby supporting subsequent research and practice in multi-disaster hotspot identification and finer-scale geospatial analysis.

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

630 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

635 The authors declare that they have no conflict of interest.

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