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EM-DAT: the Emergency Events Database

Damien Delforge [a,*], Valentin Wathelet [a], Regina Below [a], Cinzia Lanfredi Sofia [a], Margo Tonnelier [a], Joris A.F. van Loenhout [a,b], Niko Speybroeck [a]

[a] *Institute of Health and Society (IRSS), University of Louvain (UCLouvain), Clos Chapelle-aux-champs 30, Woluwe St Lambert, 1200, Brussels, Belgium*
[b] *Department of Epidemiology and Public Health, Sciensano, Rue Juliette Wytsman 14, Ixelles, 1050, Brussels, Belgium*

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ABSTRACT

The Emergency Events Database (EM-DAT) compiles global disaster data resulting from technological and natural hazards. EM-DAT details the human and economic impacts from 1900 to present, with systematic recording since 1988. Serving the humanitarian, disaster risk reduction, and academic sectors, EM-DAT's transition to open access and climate change concerns have expanded its reach and visibility. The dataset, freely available for non-commercial purposes, offers structured tabular data categorized by hazard type and standardized by individual disaster events at the country level. Data collection and validation involve daily monitoring and manual processing of textual documents from predefined sources, searching for additional sources, and conducting periodic thematic updates. With over 26,000 unique disaster entries, approximately two-thirds of EM-DAT records relate to natural hazards, predominantly floods. Although initially rooted in Health Sciences, EM-DAT's historical use cases increasingly reflect applications in Earth, Environmental, and Social Sciences, paralleling heightened global concern around climate impacts and disaster risk understanding. The evolution of EM-DAT's data content mirrors societal and technological advancements in disaster reporting. Despite these improvements, known inconsistencies and biases in data quality have been reported. Aside from providing a detailed description of EM-DAT, this article acknowledges existing limitations, discusses their implications for research and decision-making, and identifies future opportunities to enhance disaster loss databases.

1. Introduction

The EM-DAT Emergency Events Database (www.emdat.be) was established in 1988 by the Centre for Research on the Epidemiology of Disasters (CRED) at the *Université catholique de Louvain* (UCLouvain) [1]. Originally a collaboration with the World Health Organization (WHO), EM-DAT was part of a broader global emergency management data integration system [1–4] and was primarily intended for decision-makers and policymakers to support disaster preparedness and emergency management [1,5]. In EM-DAT, disasters are defined as events that overwhelm local capacity, meeting at least one of the following criteria.

1 10 deaths or above.
2 100 people affected or above.

* Corresponding author.
E-mail address: damien.delforge@uclouvain.be (D. Delforge).

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3 A call for international assistance or a declaration of a state of emergency.

Globally and for each country, EM-DAT provides data on disaster occurrences and their human and economic impacts. As of August 2024, EM-DAT has recorded over 26,700 disasters from both natural and technological hazards since 1900. EM-DAT's data collection is a manually supervised process involving significant human oversight. Systematically, the EM-DAT staff manually reviews a list of pre-identified sources, including reports and catalogs from United Nations (UN) organizations, humanitarian agencies, non-profit

Table 1
Description of EM-DAT archived public table columns.

Column Name	Description
DisNo.	Unique 8-digit identifier including the year (4 digits) and a sequential number (4 digits), with the ISO country code appended.
Historic	Binary field specifying whether the disaster happened before 2000. Data before 2000 should be considered of lesser quality.
Classification Key	A unique 15-character string identifying disasters in terms of the Group Subgroup Type and Subtype classification hierarchy.
Disaster Group	The disaster group, i.e., 'Natural' or 'Technological.'
Disaster Subgroup	The disaster subgroup.
Disaster Type	The disaster type.
Disaster Subtype	The disaster subtype.
External IDs	List of identifiers pointing to external services and resources, such as the disaster Global Identifier (GLIDE) number.
Event Name	Short specification for disaster identification, e.g., storm names (e.g., 'Mitch') plane type in air crash (e.g., 'Boeing 707'), disease name (e.g., 'Cholera'), or volcano name (e.g., 'Etna').
ISO	The International Organization for Standardization (ISO) 3-letter code referring to the Country. The ISO 3166 norm is used.
Country	Country where the disaster occurred and had an impact using names from the UN M49 Standard.
Subregion	Subregion where the disaster occurred based on UN M49 standard.
Region	Region where the disaster occurred based on UN M49 standard.
Location	Geographical location name as specified in the sources, e.g., city, village department, province, state, or district.
Origin	Additional specifications on the contextual factors that led to the event, e.g., 'heavy rains' for floods or 'drought' for a forest fire.
Associated Types	List of secondary disaster types cascading from or co-occurring aside from the main type, e.g., a landslide following a flood or an explosion after an earthquake.
OFDA Response	Binary field specifying whether the Office of US Foreign Disaster Assistance (OFDA) responded to the disaster.
Appeal	Binary field specifying whether there was a request for international assistance from the affected country.
Declaration	Binary field specifying whether a state of emergency was declared in the country.
AID Contribution	The total amount (in thousands of US$ at the time of the report) of contributions for immediate relief activities to the country in response to the disaster, sourced from the Financial Tracking System of OCHA (1992–2015). Not maintained after 2015.
Magnitude	Value related to the intensity of a hazard depending on the disaster type.
Magnitude Scale	The associated unit for the Magnitude column.
Latitude	North-South coordinates mainly for earthquakes and volcanic activity. Sometimes reported for floods, landslides, and storms (mostly when associated with floods).
Longitude	East-West coordinates mainly for earthquakes and volcanic activity. Sometimes reported for floods, landslides, and storms (mostly when associated with floods).
River Basin	Name of affected river basins typically used for floods.
Start Year	Year of occurrence of the disaster.
Start Month	Month of occurrence of the disaster.
Start Day	Day of occurrence of the disaster.
End Year	Year of disaster conclusion.
End Month	Month of conclusion of the disaster.
End Day	Day of conclusion of the disaster.
Total Deaths	Total fatalities (deceased and missing combined).
No. Injured	Number of people with physical injuries, trauma, or illness requiring immediate medical assistance due to the disaster.
No. Homeless	Number of people requiring shelter due to their houses being destroyed or heavily damaged during the disaster.
Total Affected	Total number of affected people (No. Injured, No. Affected, and No. Homeless combined).
Reconstruction Costs ('000 US$)	Costs for replacement of lost assets in thousands of US dollars ('000 US$).
Reconstruction Costs, Adjusted ('000 US$)	Reconstruction Costs ('000 US$), adjusted for inflation using the Consumer Price Index (CPI).
Insured Damage ('000 US$)	Economic damage covered by insurance companies in thousands of US dollars ('000 US$).
Insured Damage, Adjusted ('000 US$)	Insured Damage ('000 US$) adjusted for inflation using the Consumer Price Index (CPI).
Total Damage ('000 US$)	Value of all economic losses directly or indirectly due to the disaster in thousands of US dollars ('000 US$).
Total Damage, Adjusted ('000 US$)	Total Damage ('000 US$) adjusted for inflation using the Consumer Price Index (CPI).
CPI	Consumer Price Index from OECD used to adjust US$ values for inflation relative to Start Year.
Admin Units	Collection of impacted Administrative Units from the FAO GAUL 2015 referential. Individual objects correspond to Level-1 or Level-2 Administrative Units. Geocoding is maintained for non-biological natural hazards from 2000 onwards.
Entry Date	The day on which the event record was created in EM-DAT.
Last Update	The last date of modification of the event or one of its associated records in EM-DAT.

organizations, research institutes, reinsurance groups, and press agencies, supplemented with information from other sources found through active internet searches. This methodology has been employed for over 35 years. Before the 1990s and the rise of the internet, however, the data was sourced from a limited number of printed materials. The foundational content of the database was mainly data from the United States (US) Office of Foreign Disaster Assistance (OFDA) [6], established in 1964 and currently known as the Bureau for Humanitarian Assistance (BHA), within the US Agency for International Development (USAID).

For years, the data was available as online summaries or country profiles. Since 2020, the EM-DAT public data portal has offered free access to its data for non-commercial use upon registration. As of December 17, 2024, more than 92,000 users have registered. 82 % of all EM-DAT users are part of academic institutions, universities, and non-profit research institutions. These figures underscore the widespread interest in EM-DAT data within the academic and scientific community, with usage ranging from anecdotal references to disaster figures to more substantial, in-depth analyses and applications of the data.

Over time, EM-DAT has played a pivotal role in advancing a comprehensive understanding of disaster risks, i.e., beyond emergency management. Nowadays, EM-DAT is also particularly relevant to the monitoring of Disaster Risk Reduction (DRR) global agendas [7–9] and other UN institutions disaster-risk-related activities [10–14]. The current global DRR agenda under the UN is the 2015–2030 Sendai Framework for Disaster Risk Reduction (SFDRR) [9]. EM-DAT's data directly relate to SFDRR Targets A to C, aiming to reduce (A) global disaster mortality, (B) the number of people affected globally, and (C) economic losses relative to the Gross Domestic Product (GDP). SFDRR targets and indicators also intersect with those of the UN Sustainable Development Goals (SDGs), in particular, poverty (SDG-1), sustainable cities and communities (SDG-11), and climate action (SDG-13), articulating the interconnections between disaster risks, sociodemographic factors, and climate change [15].

In general, EM-DAT's rising prominence can be attributed to its longevity and progressive shift to open access, a general increasing focus on climate-related disasters, and its unparalleled position in the limited landscape of available disaster impact data [16]. Ease of use, large scope, and global coverage also contribute to EM-DAT's attractiveness, accessible as a user-friendly *xlsx* file encompassing a wide range of disaster types for each country. Beyond EM-DAT, only the UNDRR Sendai DesInventar database is an open-access multi-hazard disaster impact database tailored for global coverage. The other global alternatives covering multiple hazards are Munich Re's NatCatSERVICE and Swiss Re's Sigma, which belong to the reinsurance sector and mostly provide data summaries without public access [16]. Compared to EM-DAT, DesInventar offers a higher spatial accuracy by disaggregating impact data into administrative units within a specific country [16]. However, as it relies on voluntary contributions, DesInventar spatiotemporal coverage is irregular, albeit improving under the SFDRR agenda.

While being the most comprehensive available solution, EM-DAT is not free from missing events, values, and biases arising from the complexities of monitoring disaster impact data [4,17–24], which can also be overlooked in the scientific literature [25]. Even though comprehensive knowledge of natural hazards may be derived from other data sources, such as seismological data or meteorological reanalyses, challenges remain in accurately capturing the human side of disasters, mortality, or other human and economic impacts [26,27].

Given EM-DAT's extensive history, this publication aims first to update and replace the seminal yet outdated 1992 EM-DAT overview paper [4] with a technical note that accurately reflects the current data content, structure, and available services. Secondly, it summarizes existing EM-DAT use cases, discusses known limitations and their implications, and identifies opportunities to improve the utilization of disaster loss data for enhanced disaster risk understanding and management.

2. Data collection methods

EM-DAT collects disaster data from various sources, following several documentation routines. Among all the collected figures found in the sources, the validation routines control what information is being published to the end user.

2.1. Collected data

The EM-DAT team processes textual documents, referred to as sources, to extract data about the disaster type, the timing and location of the event, and the impact figures per country. In complement to this section, we refer to Table 1 for a column-based description of the dataset served to the users in December 2024 [28].

Disasters are hierarchically classified in a four-level classification tree, from disaster groups to subtypes (Table 1). For disasters related to natural hazards, the classes are based on the Integrated Research on Disaster Risk Peril Classification and Hazard Glossary [29]. Event start and end dates and locations are directly extracted from sources, with countries identified using a three-letter standard country code following the ISO-3166 standard [30]. Standardization for region, subregion, and country names follows the UN M49 standard [31]. For non-biological natural hazards occurring after 2000, additional spatial information is provided up to the second administrative level of the 2015 Global Administrative Unit Layers (GAUL) by the Food and Agriculture Organization (FAO). However, while EM-DAT references GAUL units identified from locations mentioned in the sources, the impact figures are not distributed among them.

Human impact data include the total number of deaths, including long-term missing individuals, and the count of total affected individuals, which combines numbers of injured, homeless, and otherwise affected individuals, where the concept of otherwise affected people is less explicit than that of injured and homeless individuals. Whenever possible, EM-DAT numbers are reported as specified in the sources. However, based on regional demographic statistics updated by the United Nations Development Programme [32], the EM-DAT team estimates the number of people impacted when it is expressed in terms of impacted housing units or families. Likewise, when a source refers to an order of magnitude, such as 'thousands affected,' they are entered in the database as the minimal suggested amount. For example, in such cases, 2000 people affected would be encoded.

Economic impact figures in EM-DAT include the total damage estimated by the sources, converted into US$ at the time of the disaster. Less frequently, EM-DAT includes figures for insured damage and reconstruction costs, also in US$. To account for the effect of inflation on economic loss figures, EM-DAT also provides values adjusted using the Consumer Price Index (CPI) provided by the Organisation for Economic Cooperation and Development.

As a living project, EM-DAT's data processing and structuring methods have evolved since EM-DAT's inception in 1988, particularly concerning disaster classification systems and definitions due to interactive discussions with stakeholders and researchers [4,29,33,34]. For information on tracking changes, updates, versioning, and identifiability, we refer to the Data & metadata access section.

2.2. EM-DAT sources

The sources utilized in EM-DAT are not displayed in the public records for various reasons, including legal considerations, preserving the integrity of services EM-DAT depends on, and upholding neutrality, especially when dealing with potentially politically sensitive data. However, Table 2 and Fig. 1 provide a summarized overview of the sources collected following the process described in the Documentation routines section for the 2000–2023 period. The table features the top-20 sources that reference at least one figure contributing to the three primary impact variables in the EM-DAT public table: Total Deaths, Total Affected, and Total Damage (Table 1). The top 20 covers 97 % of the total number of entries, as defined in Table 2 for the 2000–2023 period.

EM-DAT's paid subscription to *Agence France Presse* (AFP) provides extensive coverage of disasters. In particular, AFP is important in EM-DAT to track disasters of lower impact and, therefore, of higher frequency. Within the Press group, AFP is the primary source, selected around 50 % of the time when documenting a disaster, except for total economic damage (Fig. 1d). Data from the International Federation of Red Cross and Red Crescent Societies (IFRC), with its emphasis on humanitarian aspects, is invaluable for documenting the health impacts of disasters (Fig. 1b and c). In 90 % of cases, IFRC sources provide figures relative to the total number of affected people (Fig. 1c), and, in 65 % of cases, IFRC sources indeed contributed to the calculation of the Total Affected variable (Table 1) in the published records. A similar pattern is observed for OCHA sources or the less frequent 'Government' category, a grouped category that consolidates official reports from various governmental bodies and institutions. Reinsurance reports provide vital insights into economic damage (Fig. 1d), though they play a lesser role in detailing affected populations (Fig. 1c). Contributions from UN or US/EU sources display no consistent pattern. However, OFDA/BHA, part of the US/EU group, is a key source for historical data, primarily before 2000 [6]. ECHO transitioned from a complementary source to a systematic one in 2019, resulting in a noticeable increase in contributions from the US/EU group that year (Fig. 1a). Notably, the source system for EM-DAT is dynamic; certain systematic sources have either ceased to be used or have become obsolete for practical reasons (Table 2). This non-stationarity introduces uncertainties and potential biases in data quality, as further discussed in the Limitations & perspectives section.

Table 2
Overview of EM-DAT top-20 sources for the 2000–2023 period.

Short Name	Full Name	Group	Documentation Routine	Hazard Restriction	No. Entries
AFP	*Agence France Presse* (Paid Subscription)	Press	Systematic	None	9366
AON	AON Catastrophe Reports	Reinsurance	Systematic	Natural	3116
SwissRe	Swiss Re Reports	Reinsurance	Systematic	None	2999
IFRC	International Federation of Red Cross and Red Crescent Societies	IFRC	Systematic	None	2620
DFO	Dartmouth Flood Observatory	Research	Systematic	Floods	2064
Lloyds Cas Wk	Lloyd's Casualty Magazine (Paid Subscription)	Reinsurance	Systematic[b]	Natural	1936
ECHO	European Civil Protection and Humanitarian Aid Operations	US/EU	Systematic	Natural	1718
OCHA	United Nations Office for the Coordination of Humanitarian Affairs	UN	Systematic	Natural	1404
MunichRe	Munich Re Reports	Reinsurance	Systematic	Natural	1067
NOAA[a]	National Oceanic and Atmospheric Administration	US/EU	Systematic	Natural	898
WHO[a]	World Health Organization	UN	Systematic	Epidemics	857
OFDA/BHA	Office of US Foreign Disaster Assistance (OFDA) now the Bureau for Humanitarian Assistance (BHA)	US/EU	Systematic	None	716
FloodList	FloodList	Other	Systematic	Floods	643
USGS	United States Geological Survey	US/EU	Systematic	Earthquakes	503
IRIN	IRIN News, now The New Humanitarian	Press	Systematic[b]	None	428
Government[a]	National reports from governments	Other	Complementary	None	402
Wikipedia	Wikipedia the Free Encyclopedia	Other	Complementary	None	271
CAT-i	GuyCarpenter Catastrophe Insights Library	Reinsurance	Systematic[b]	None	186
REDLAC	Regional Group on Risks Emergencies and Disasters for Latin America and the Caribbean	UN	Systematic[b]	None	171
WFP	World Food Programme	UN	Systematic	None	166

[1] Groups are defined for reporting purposes and do not represent structural elements in EM-DAT.
[2] This table links an entry to a source if it mentions a figure relevant to Total Deaths, Total Affected, or Total Damage (Table 1), regardless of whether the figure is selected for public display. Reference date: 2024-12-04.
[a] These sources refer to multiple information channels or services grouped for reporting purposes.
[b] These systematic routines stopped in 2009 (Lloyds Cas Wk), 2015 (IRIN, REDLAC), 2016 (CAT-i).

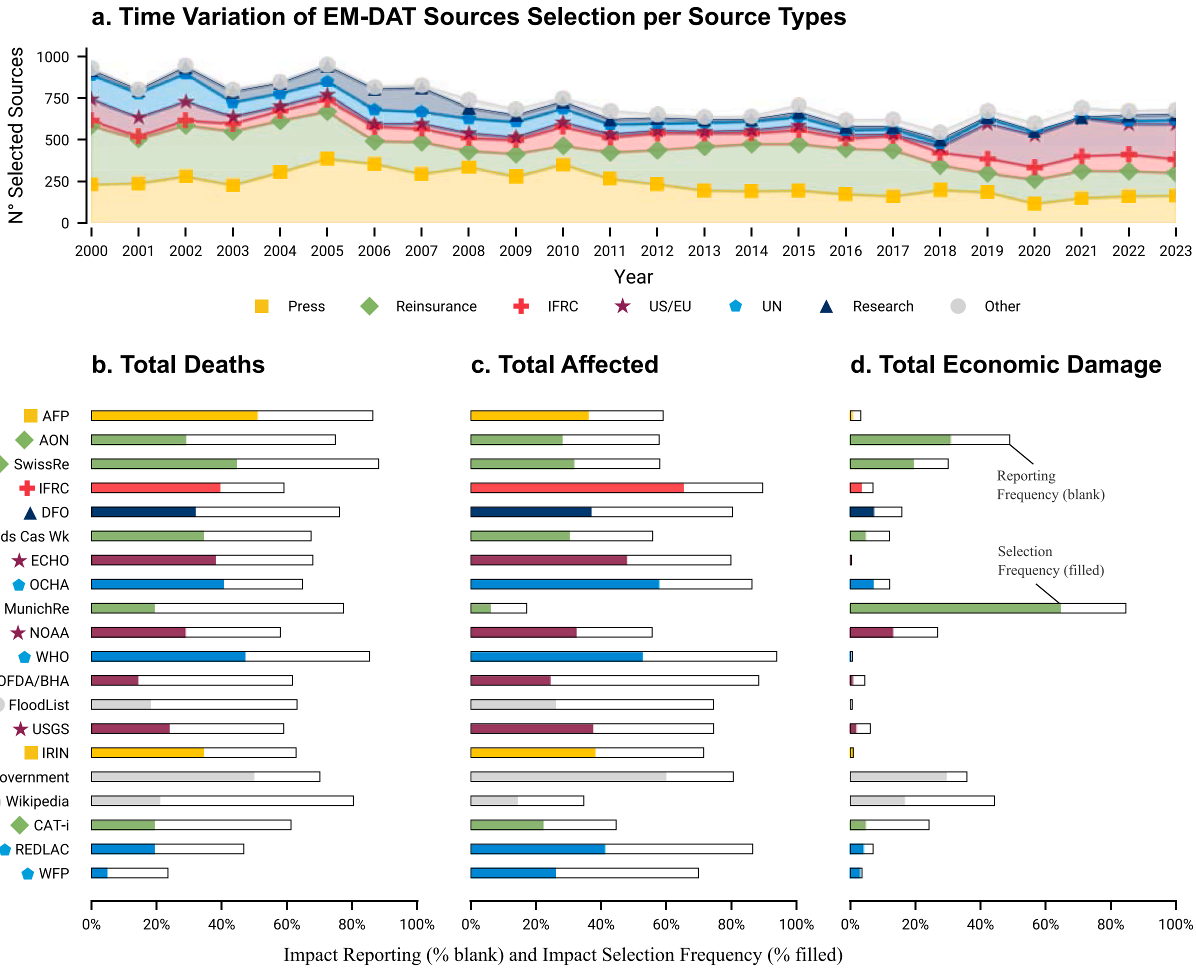

Fig. 1. Overview of selected sources in EM-DAT for the 2000–2023 period. (a) Stacked time series of the temporal evolution of grouped selected sources. Selected sources are sources that document a disaster with impact figures contributing to at least one of the variables—Total Deaths, Total Affected, or Total Damage—in the EM-DAT public table (Table 1). Each source group, denoted by a unique symbol and color, corresponds to the categories used in Table 2. The bottom sub-panels detail the frequency at which sources from the top-20 list (Table 2) document (blank bar) or are being selected (filled bar) to contribute to EM-DAT published impact variables: (b) Total Deaths, (c) Total Affected, and (d) Total Damage. The percentage (x-axis) of documentation or selection is calculated relative to the 'N° Entries' column in Table 2. The color used for the filled bar maps to the source group colors used in the top-panel panel (a).

2.3. Documentation & validation routines

Validation routines systematically begin with documentation routines to ensure completeness and the latest updated status of the collected data. Subsequently, the validation process continues by selecting figures for display in each entry of the public dataset and confirming that the entries meet EM-DAT criteria for publication. We distinguish three manually supervised validation routines following different time frames: monthly (B1, Fig. 2) and annual validations (B2), as well as thematic reviews (B3).

Every month, as part of the monthly validation (B1), a complementary documentation routine (A2) completes the data added continuously during the month with systematic routines (A1). Any disaster that was still ongoing during the previous validation is also reviewed. Then, the EM-DAT team proceeds with the selection of the figures for public display. This selection and the subsequent prioritization of some sources over others are influenced by various factors: the figure itself, the area and period it covers, the chronology of the sources, and their reliability, with a preference for institutional or scientific sources over press sources. This attribution task is both complex and case-specific, and the defined guiding rules are voluntarily kept flexible, leaving the final decision to the discretion of the EM-DAT team. We refer to Fig. 1b to d to highlight what sources tend to be selected relative to what impact. Finally, if a private entry happens to meet the EM-DAT entry criteria, i.e., at least ten deaths, 100 affected persons, or a national or international emergency situation, its status is updated to 'public.' EM-DAT further imposes that at least two distinct sources are attached to the entry to be set public. A newly added or updated entry will be accessible to users by the following week.

The annual validation (B2) is conducted during the January–February period, scoping the preceding year's data before publishing the annual report. This routine involves both systematic and complementary documentation processes (A1, A2) for all events from the

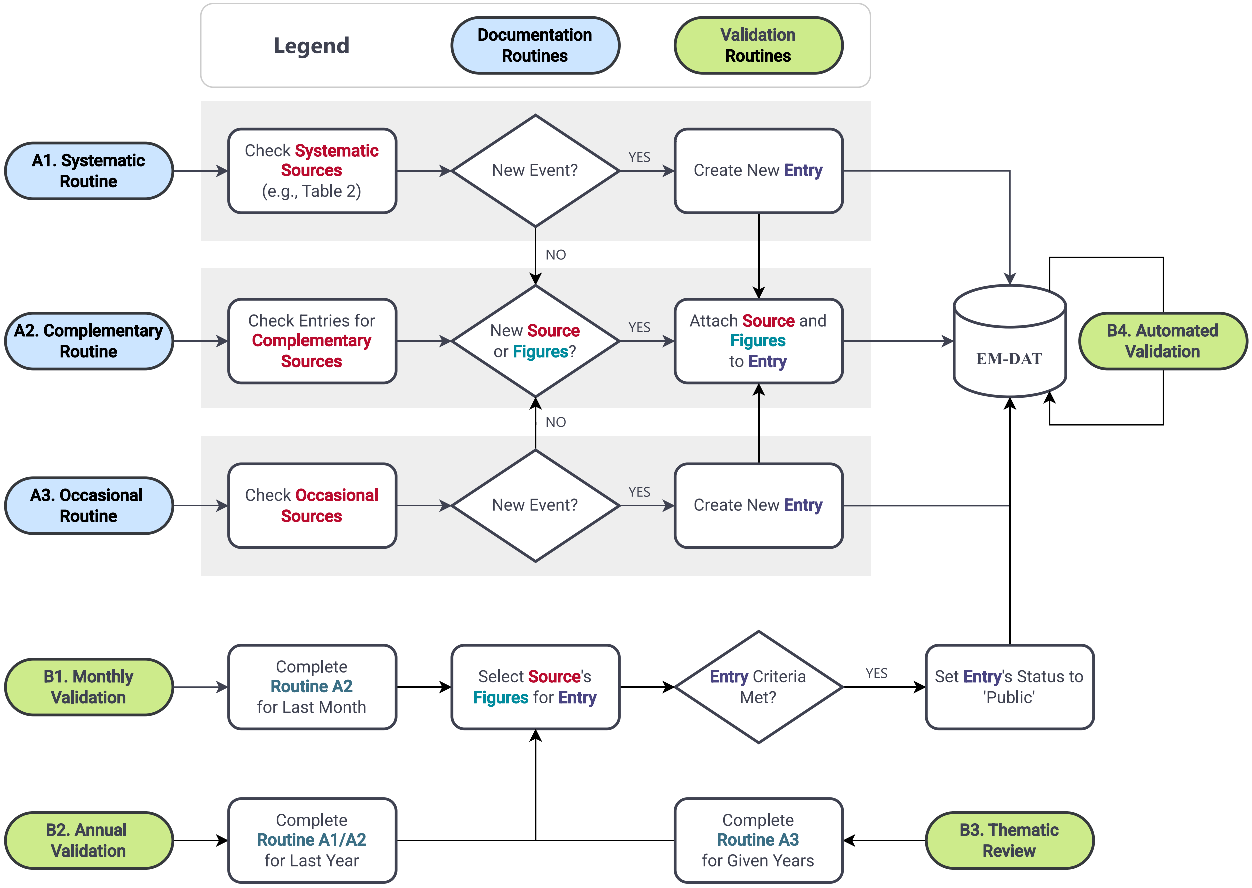

Fig. 2. Flowchart of the EM-DAT data acquisition and validation routines. Documentation routines (A1 to A3) compile disaster-related textual documents (sources), controlled manually. The systematic routine (A1) reviews a list of predefined sources (systematic sources). The complementary routine (A2) looks for complementary, i.e., not predefined, sources documenting disaster entries through active internet searches. The occasional routine (A3) involves a sporadic reviewing process coupled with a thematic review, focusing either on a specific disaster type, impact, other data attributes, or source type. The supervised validation routines (B1 to B3) organize the documentation routines, select data for public display, and ensure entry criteria are met for publication. Three supervised validations are conducted monthly (B1), annually (B2), or sporadically for thematic reviews (B3). Automated validation represents the built-in constraints in the data entry interface and database model, along with programmatic ways for error identification and warning issuance. This flowchart was created using diagrams.net.

previous year, as well as those that were ongoing the prior year. In contrast, thematic reviews (B3) are conducted once or more per year and are associated with occasional documentation routines (A3) that cover a diverse range of topics. Consequently, reviews focusing on the same topic are spread over multiple years.

As of September 2023, updates to the database model and data entry interface have introduced enhanced systems to automatically prevent the manual encoding of forbidden or incorrect values or formats (B4). Occasionally, errors in the EM-DAT database may not be related to impossible values or formats, such as duplicated events or typographical errors in text or numbers [23]. To address these issues, automated validation routines also generate warnings to highlight anomalies and potential errors. These automated routines check for potential duplicated events based on their location and timing and ensure the consistency of date and time fields, latitude and longitude values, and hazard magnitude values. These procedures are progressively updated as users identify or report errors. Although these are privately integrated into the database operations, a public and complementary testing framework was developed in 2024 to improve the transparency and reproducibility of data testing while operating on the public table served to the users [35].

3. Data & metadata access

The EM-DAT data can be accessed from different data products provided under different conditions and for different purposes. We describe hereafter the two most detailed data products, illustrating the database content using an official archive of the dataset.

3.1. The EM-DAT living dataset

Since 2020, the EM-DAT data can be downloaded as an *xlsx* file from the EM-DAT public portal (https://public.emdat.be), upon registration and acceptance of the condition of use. The public portal is the endpoint for the latest EM-DAT data, updated weekly, although data may not have been through the entire validation process (see Documentation & validation routines). The EM-DAT Living Dataset is complemented by a documentation portal (https://doc.emdat.be), released in September 2023. The documentation portal features rich and detailed information about data product accessibility, a changelog history, the database and dataset description, the data collection protocols, discussions on the known issues and limitations, and additional resources and tutorials. The EM-DAT living dataset is free for research and non-commercial use, with a commercial license available. The EM-DAT Living Dataset cannot be redistributed without prior permission to encourage the use of the second data product when redistribution is required.

Given that the EM-DAT Living Dataset and portal are regularly updated, the reader is referred to the documentation portal for the latest information on data accessibility, products, file formats, and protocols. The portal also includes Python tutorials to assist programmers with handling and visualizing EM-DAT data, with plans to release additional tutorials for other programming languages. For non-programmers or users unfamiliar with *xlsx* file formats, the EM-DAT team has developed a lightweight open-source dashboard to facilitate visual exploration of the EM-DAT *xlsx* files [36].

3.2. The EM-DAT archive

The EM-DAT Archive features archived versions of the EM-DAT Living Dataset, i.e., a specific snapshot in time exported along with its documentation. The EM-DAT Archive is hosted at UCLouvain using the Dataverse open-source research data repository software. The EM-DAT Archive is meant to align with the FAIR principles of Findability, Accessibility, Interoperability, and Reusability (FAIR) [37] and is, therefore, the preferred dataset to align with open and reproducible science practices.

The EM-DAT Archive was initiated at the end of 2024, alongside this article, with the first version of the dataset covering the EM-DAT data for the 1900–2023 period [28], passing the tests developed in the validation framework [35] and redistributable under CC-BY-NC-ND conditions [38]. This archived version contains more than 26,000 public entries from 1900 to 2023.

3.3. Content overview & external references

Fig. 3a provides an overview of the EM-DAT content distribution by hazard types, following the third level of the EM-DAT classification tree. 64 % of EM-DAT disasters belong to the 'Natural' group, most of which refer to floods (22 %) and storms (18 %). Within the remaining 36 % of 'Technological' hazards, transport accidents (road, water, air, and rail) are the most frequent.

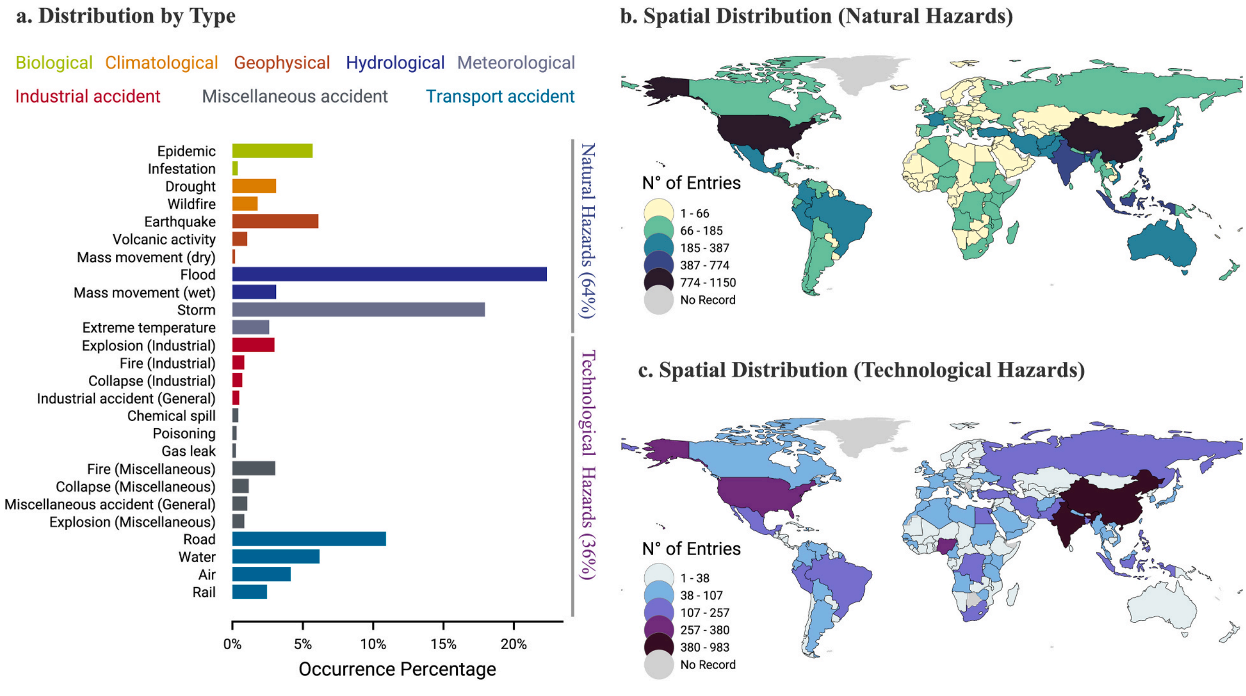

Fig. 3. Overview of disaster occurrences in EM-DAT. (a) Distribution by hazard types. (b) Spatial distribution of disasters in the Natural group. (c) Spatial distribution of disasters in the technological group. The figure is based on the 26,368 disasters of the EM-DAT 1900–2023 Archived Dataset [28]. The classification system displayed in panel (a) corresponds to the EM-DAT third classification level (Disaster Type in Table 1). Disasters related to types with fewer than 10 occurrences are not reported in panel (a).

Fig. 3b and c illustrate the spatial distribution of EM-DAT disasters from natural and technological groups. The EM-DAT database content has been documented at local, regional, and global levels, either broadly or with a focus on specific hazard types. At the global level, for example, Shen & Hwang (2019) [39] and Tin et al. (2024) [40] provide an analysis of disasters in the 'Natural' group over the period 1900–2015; Cvetković et al. (2024) [41] and Shen & Hwang (2018) [42] also include disasters of technological origin; Donatti et al. (2024) [43] focus on climate-related disasters, highlighting sub-national patterns.

Since disaster patterns and data quality can vary by region, time period, hazard type, impact type, or event magnitude, readers are encouraged to explore these analyses further, consult additional studies, or conduct their own targeted investigations. Readers can explore the content of an official EM-DAT file without programming skills using the EM-VIEW Disaster Dashboard [36]. This dashboard allows customization of bar charts, maps similar to those in Fig. 3, and time series, with filtering options on disaster types, periods, regions, and countries.

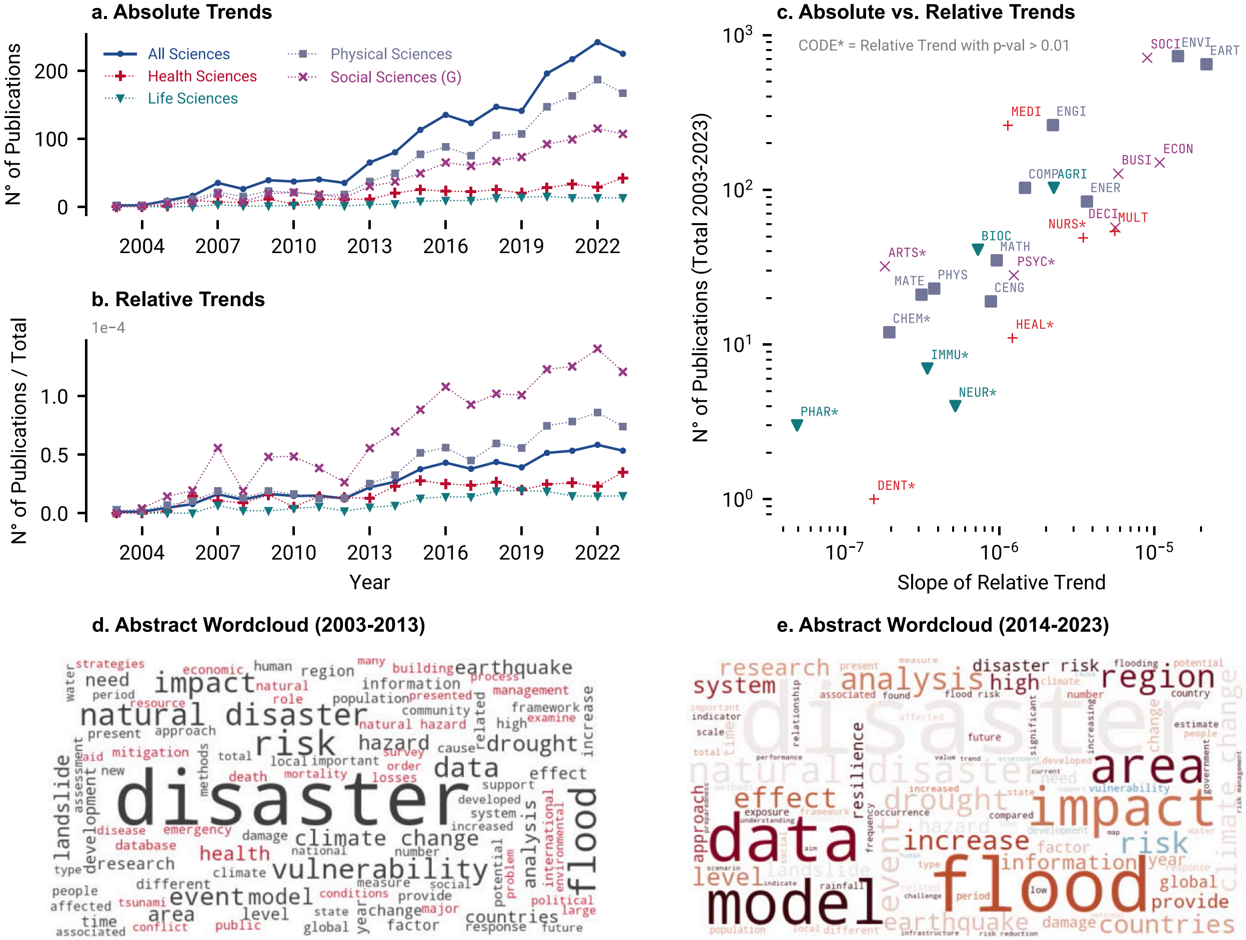

Fig. 4. Summarized patterns of scientific articles (n=1915) referring to EM-DAT in the Scopus scientific literature database (2003–2023). (a) Absolute temporal pattern: yearly count of publications referring to EM-DAT across all domains (All Sciences) or within specific Scopus-defined domains (Health, Life, Physical, Social Sciences). (b) Relative temporal pattern: same as (a) normalized by the total number of publications in each domain for that year. (c) Scatterplot of the linear slope of relative trends computed for each Scopus subject area against the total number of publications in these areas over 2003–2023. The marker indicates the domain of the subject area using the panel (a) symbols. Asterisks * denote relative-trend slopes that are not significant (p-value >0.01), given a Wald Test as implemented in SciPy [44]. (d) Word cloud of the 100 most frequent words in abstracts for the 2003–2013 period, scaled relative to the most frequent word, with words absent from the top 100 of the 2014–2023 period displayed in orange. (e) Similar word cloud for the 2014–2023 period, with a color scale indicating increases (red) or decreases (blue) in relative frequencies compared to the 2003–2013 period. Data source: the corpus was obtained from the base Scopus query 'DOCTYPE (ar) AND (TITLE-ABS-KEY (em-dat) OR REF (em-dat))', further declined by subject areas and publication years, and processed using pybibliometrics [45]. Subject area codes: MEDI: Medicine, NURS: Nursing, VETE: Veterinary, DENT: Dentistry, HEAL: Health Professions, MULT: Multidisciplinary, AGRI: Agricultural and Biological Sciences, BIOC: Biochemistry, Genetics and Molecular Biology, IMMU: Immunology and Microbiology, NEUR: Neuroscience, PHAR: Pharmacology, Toxicology and Pharmaceutics, CENG: Chemical Engineering, CHEM: Chemistry, COMP: Computer Sciences, EART: Earth and Planetary Sciences, ENER: Energy, ENGI: Engineering, ENVI: Environmental Sciences, MATE: Material Sciences, MATH: Mathematics, PHYS: Physics and Astronomy, ARTS: Arts and Humanities, BUSI: Business, Management and accounting, DECI: Decision Sciences, ECON: Economics, Econometrics and Finance, PSYC: Psychology, SOCI: Social Sciences.

4. EM-DAT applications and use cases

4.1. In the scientific literature

4.1.1. Synthetic overview

Fig. 4 provides a descriptive overview of how EM-DAT has been utilized within the scientific community by analyzing peer-reviewed articles citing EM-DAT in the Scopus database. These articles, termed 'EM-DAT publications,' were published between 2003 and 2023 and mentioned 'EM-DAT' in the title, abstract, keywords, or references. Over these two decades, the number of EM-DAT publications has increased, reaching up to 250 articles per year (Fig. 4a). Most of these publications fall within the Scopus domains of Physical Sciences, followed by Social Sciences. By normalizing the number of EM-DAT publications against the annual total for each Scopus domain, changes can be observed in the relative interest in EM-DAT. For instance, Fig. 4b shows a notable relative increase in Social Sciences. Fig. 4c summarizes trends in specific subject areas within the domains. Within Physical Sciences, the main contributing subject areas are Environmental Sciences (ENVI) and Earth and Planetary Sciences (EART), followed by Engineering (ENGI), Energy (ENER), and Computer Sciences (COMP) as leading contributors (Fig. 4c). In Scopus, Social Sciences is both considered a domain and a specific subject area (SOCI, Fig. 4c), which, along with Economics, Econometrics, and Finance (ECON), Business, Management, and Accounting (BUSI), and Decision Sciences (DECI), make up the most significant contributions to EM-DAT Social Sciences trends (Fig. 4a and b).

Despite EM-DAT's origins as a public health initiative, there has been little to no substantial change in the absolute or relative number of EM-DAT publications in Health Sciences over the past decade. A similar observation holds for the Life Sciences domain. However, some specific subject areas within these domains remain significant (Fig. 4c). For instance, Medicine (MEDI) accounts for over 200 documents, and Nursing (NURS) and Multidisciplinary Health Sciences (MULT) are showing upward trends. Within the Life Sciences domain, Agricultural and Biological Sciences (AGRI) stands out among the other fields in the group.

The word clouds in Fig. 4d and e highlight that the focus of EM-DAT publications remains predominantly on disasters related to natural hazards, particularly floods, which have gained significant interest (Fig. 4e). This aligns with the most frequent disaster type in EM-DAT (Fig.3a). Additionally, droughts, earthquakes, and landslides are also prominent, with their relative interest remaining stable (Fig. 4d and e). During the 2003–2013 period, words such as "health," "aid," "conditions," and "emergency" appeared frequently. However, they have fallen out the top 100 in the 2014–2023 period, giving more prominence to words like "model," "data," "impact," "area," and "region." This shift emphasizes the relative decline in the share of EM-DAT publications within Health Sciences and an increasing focus on data, risk and impact modeling, and broader-scale analyses.

Referring to the EM-DAT database does not imply that EM-DAT is directly utilized as part of an empirical research study. Jones et al. (2023) have highlighted 433 papers that used EM-DAT as a primary or secondary data source between 1996 and 2021, over a selected sample of 1727 referring to EM-DAT, with article authors, titles, years, and journal names available in their supplementary materials for further inquiry [25]. Accordingly, EM-DAT was used 75 % of the time for contextualizing or discussing results and 25 % as part of the methodology.

4.1.2. Example uses

Analyzing disaster losses – either alone or as part of composite vulnerability and risk indicators – remains one of the primary applications of the EM-DAT data, which provides insight into risk profiles at local and regional levels [46–50] or globally [39–43, 51–55], whether in general or for specific hazard or loss types. The EM-DAT impact data has also been used and related to specific domain concerns. Examples include reassessing humanitarian logistics [56–58], evaluating the effect of hazard exposure on child health [59–61], understanding losses related to El Niño–Southern Oscillation patterns [62,63], exploring disaster effects on sectors such as tourism [64], trade, in particular, impact on food exports and agriculture [65–69], or the evaluation and optimization of forecast models and early warning systems [70–72].

Two intertwined additional use cases relate to limitations and perspectives around EM-DAT (Section 5). The first focuses on comparative studies between disaster loss databases [23], primarily comparing EM-DAT with existing local data sources [73–77], allowing researchers to derive qualitative and quantitative insights into available and accessible disaster loss data. Additionally, EM-DAT can also provide a benchmark for evaluating new regional or hazard-specific databases [78–80].

The second use case involves instances where EM-DAT information is combined with other datasets to complement available loss data or provide a broader scope of disaster risks. Examples of datasets expanded using EM-DAT include the GDIS dataset, which provides improved geocoding for a subset of disasters in EM-DAT [81], the Unified Global Landslide Database [82], or FLODIS, a dataset integrating EM-DAT flood-related impact data with population displacement data and flood maps [83], as well as regional or local disaster catalog compilations [74,78,84,85]. Regarding enhanced risk comprehension, examples include studies that leverage EM-DAT to reanalyze hazard footprints, durations, and intensities from geospatial meteorological data [86,87], disaster exposure using population data [88], social inequalities using economic and demographic data [89], or reconstructing a multi-hazard and compound systemic view on disaster risks [90–92].

4.2. In disaster risk reduction initiatives

Tracking the use of EM-DAT beyond academic literature poses notable challenges, particularly at the national level. Although user registration data, internal surveys, and communications between the EM-DAT team and stakeholders indicate extensive non-academic applications, the database's specific impact on local disaster risk management remains unquantified. Its potential role in supporting

SDG and SFDRR indicators reporting by member states is similarly unclear.

At the global level, however, EM-DAT is frequently referenced in UN disaster-related reports [10–14]. More recently, EM-DAT data has been integrated into external data hubs that combine diverse risk-related data, including sociodemographic indicators and disaster impact information from specialized sources. Examples of such platforms include the Humanitarian Data Exchange (HDX) of the UN OCHA [93], or the Risk Data Hub of the European Commission (EU) Disaster Risk Management Knowledge Centre [94], within which EM-DAT data contributes to Index for Risk Management (INFORM), facilitating the comparison of risk profiles between countries [95].

With respect to targeted uses, EM-DAT previously served as the reference dataset for the Asian Disaster Reduction Center (ADRC) to issue the Global Unique Disaster Identifier Number (GLIDE) [96], a service now provided upon stakeholders' requests. The GLIDE system addresses the fragmentation of disaster information by assigning globally recognized unique identifiers for disasters, supported by various international organizations. These identifiers simplify data exchange, comparison, and interoperability across systems such as EM-DAT, IFRC Go, OCHA ReliefWeb, the Global Disaster Alert and Coordination System (GDACS), and the USGS Earthquake Catalogs (see External IDs column in Table 1). Following the 2004 Sumatra Earthquake and Indian Ocean Tsunami, EM-DAT data contributed to the early calibration of GDACS for impact forecasting [97,98]. Likewise, EM-DAT has been integrated into the Prompt Assessment of Global Earthquakes for Response (PAGER) system, developed by USGS, as part of the PAGER-CAT earthquake loss catalog used in the system calibration [99].

5. Limitations & Perspectives

5.1. Known limitations

Without notice, incomplete or inconsistent data in EM-DAT can undermine research and policy, hence, understanding, prioritization, and decision-making in disaster risk management and aid resource allocation, by obscuring the true frequency, severity, and costs of disasters, skewing comparisons, and distorting trends. EM-DAT has a range of limitations, many of which pertain to its fundamental design. Other limitations are related to internal data quality issues, which, while being highlighted in the literature for some time [17,18], have frequently been overlooked in research relying on EM-DAT [25]. Primarily, three types of issues arise: (i) omitted disaster events, as revealed in local case studies [73,74]; (ii) events with missing values, especially in impact variables [24,25]; and (iii) events with inconsistent or inaccurate attributes when compared to other sources [22,23,76].

Aligning with the terminology proposed by Gall (2009), disaster loss databases, in general, are subject to five types of biases:

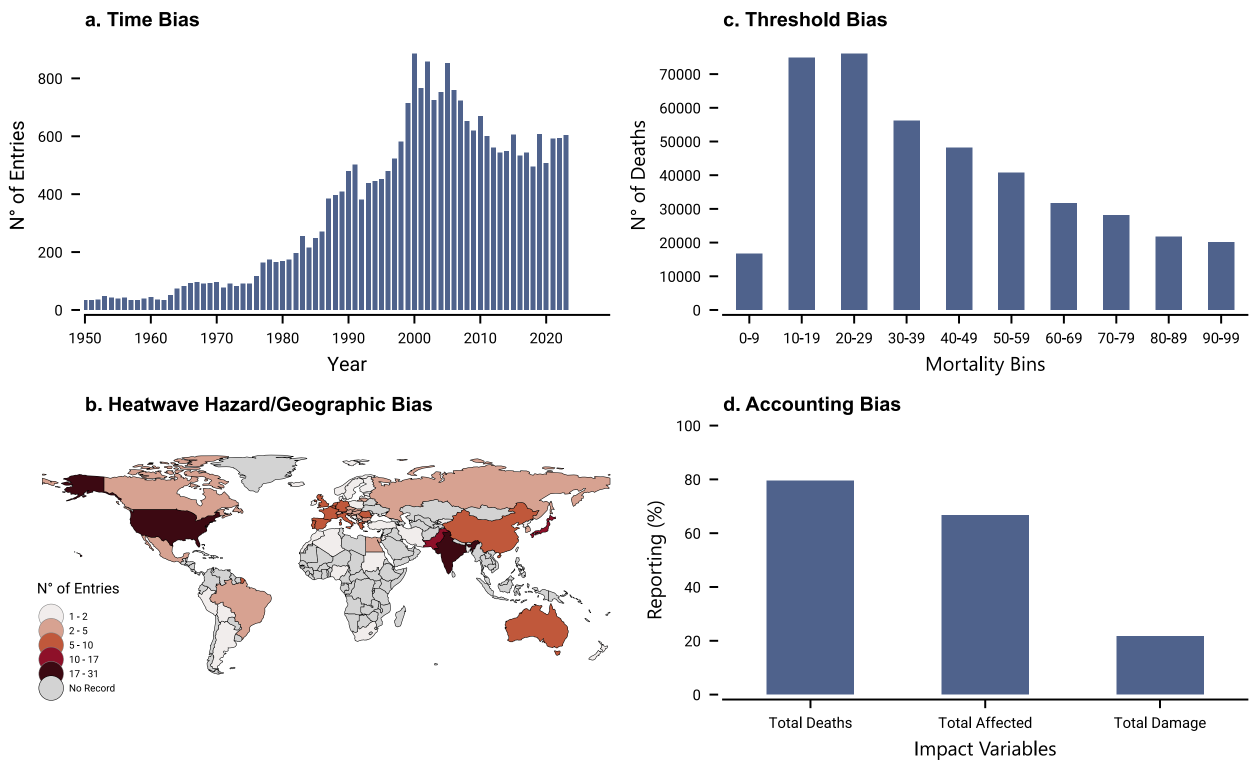

Fig. 5. Illustration of EM-DAT specific biases. (a) Time biases in the number of disaster entries per country (1950–2023); (b) Hazard-related and geographic biases illustrated for heatwave events for the full record period 1900–2023; (c) Threshold biases illustrating the visible effect of the ten-deaths inclusion criterion for the full record period 1900–2023; (d) accounting bias illustrated by the unequal reporting of the main impact variables – Total Deaths, Total Affected, and Total Damage (Table 1) – for the full record period 1900–2023. Data from the EM-DAT Archive [28].

systemic, time, geographic, hazard-related, threshold, and accounting biases [16,18]. In other words, data quality issues are affected by the design of disaster reporting systems (i.e., systemic biases) and other more representable disaster attributes such as the date of occurrence, its location, the type of hazard, its magnitude, and the type of impact monitored (Fig. 5).

5.1.1. Systemic biases

Systemic biases arise from the design and protocols of disaster reporting systems [18]. Differences among these systems contribute to discrepancies between disaster loss databases [22,23,76]. Quantifying these biases is a complex task, encompassing the broader societal context of disaster reporting. Discussions on disaster loss reporting emphasize not only the need to align systems and protocols for comparability but also the importance of making them more relevant to address current political, management, and research needs [100,101].

Disaster loss databases, such as EM-DAT, are currently unfit for certain purposes. For example, its criteria for data entry and data granularity are frequently regarded as too coarse. When analyzing exposure and vulnerability components of disaster risks, the data lacks sufficient disaggregation by administrative units or vulnerable population groups, such as age, income, or gender categories. The SFDRR and SDG agendas demand more detailed and disaggregated data to align with the principle of "leaving no one behind" [100]. Additionally, the EM-DAT classification system, with its 77 subtypes, is less detailed than the ISC-UNDRR Hazard Information Profiles published under the SFDRR agenda [102].

5.1.2. Time biases

Time biases (Fig. 5a), rooted in uneven reporting quality over time, are exacerbated by technological and institutional advancements affecting data availability [1,17,18]. Especially in the 1990s, the content of disaster loss databases was influenced by mass media, the internet as other information technology, as well as disaster management and monitoring initiatives, including the EM-DAT establishment in 1988. The time bias makes it difficult to infer insights about the evolution of disaster risks from long-term trend analysis of EM-DAT data alone, and the trend due to increased reporting capacity can sometimes be prematurely attributed to climate-driven hazard trends without controlling for the reporting bias or the sociodemographic drivers of exposure [103]. Recent studies illustrate that the increasing trends from the ’60s and 2000s are largely due to improved reporting of low-fatality events [104, 105].

5.1.3. Hazard-related biases

Hazard-related biases highlight disparities in data coverage for different hazard types. Specifically, EM-DAT shows less consistent monitoring for epidemics and temperature extremes. Pandemics have always been excluded from EM-DAT. Regarding epidemics, the EM-DAT inclusion criteria, e.g., at least ten deaths or 100 affected, are often too low and impractical for monitoring [106]. Extreme temperature events, such as heat waves, also exhibit biases in EM-DAT [107,108] (Fig. 5b). The impact of heat waves is often expressed in terms of excess mortality or relative risk, a challenging estimation in countries without civil registrations of deaths [26] or where less research is conducted [109]. Therefore, an increase in the global coverage and accessibility of civil registrations of vital statisticsand health condition data could improve disaster monitoring worldwide.

5.1.4. Threshold biases

Threshold biases refer to low-impact disasters being more likely to go unnoticed. However, their cumulative impact, if recorded, can be significant [75]. Threshold biases are inevitably reinforced through database entry criteria [18]. In Fig. 5c, the cumulative mortality impact of disasters with less than ten deaths is not null because some disasters are included based on other criteria. However, this cumulative impact overlooks the actual situation, as evidenced by the sharp difference with the cumulative mortality impact of disasters with 10–19 victims.

5.1.5. Geographic biases

Geographic biases result from spatial inconsistencies in data coverage, across boundaries [18,108], or larger areas like Sub-Saharan Africa often being less well monitored [110,111], as is the case with heatwave events (Fig. 5b). Discrepancies in reporting systems between countries further exacerbate these biases. Countries investing in disaster loss monitoring systems or with substantial international media coverage will likely be better represented in EM-DAT. In addition, EM-DAT may also exhibit distance or language biases since such biases have been studied and reported for other databases [112].

5.1.6. Accounting biases

Accounting biases refer to inconsistent reporting across different impacts. Fig. 5d illustrates the better coverage of mortality in EM-DAT compared to other losses, in particular, the economic damage, which is only specified for about 20 % of EM-DAT entries. Generally, less tangible and accountable losses tend to be underestimated. For instance, indirect and long-term impacts, such as disease outbreaks or excess mortality linked to post-disaster sanitary conditions, can be overlooked in EM-DAT since it is the case in the literature [113]. Similarly, insured damage is better covered than non-insured or indirect economic losses.

5.2. Bias mitigations and perspectives

Like human memory, EM-DAT may exhibit selective bias or incompleteness, particularly favoring recent or significant events. However, this does not diminish its instrumental value, as evidenced by the sample of use cases and applications covered in Section 4.

Effective use of EM-DAT in operations, management, or research necessitates a clear awareness of its inherent uncertainties and limitations to ensure appropriate analytical considerations and caution. Some measures to address these limitations may have direct applications, while others are long-term community efforts and strategic planning to enhance the overall reliability of the disaster loss data landscape by addressing systemic biases.

5.2.1. Bias mitigation

Jones et al. (2023) provide references and practical insights on how empirical research addresses missing values within EM-DAT [25]. While many approaches are case-specific, some general strategies have been identified, such as narrowing the scope of the analysis. Specific biases are typically intertwined, so filtering the data may alter all biases. One could, for instance, focus on a specific region or country. Regarding trends analysis, time biases are primarily a concern for the historical data under the influence of increased reporting capacity [103], especially regarding low-fatality events [104,105]. Hence, excluding historical events before 2000 or removing low-fatality events from the analysis can make a trend analysis more robust.

Kron et al. (2012) [19] have also emphasized the importance of critically assessing data by recognizing that most values are estimates rather than precise facts, validating figures through cross-checks and completions, and considering the potential sources of distortion. They also caution against relying on regression analyses without understanding the underlying data processes and highlight the need to test the sensitivity of results, as slight modifications to a dataset or a single large value can significantly alter patterns. Some cross-comparison studies and cases of EM-DAT expansions through data fusion and interoperability have been covered in Section 4 and provide time-saving conclusions or enriched datasets that can be of direct utility. While systemic biases are not directly manageable by analytical dispositions, research conclusions or decision-making can be improved by gaining insight into the operational challenges faced by managers of these databases [4,17,19,20].

5.2.2. Perspectives

EM-DAT undoubtedly owes part of its success to its longevity and continuous maintenance—strengths closely linked to its relatively simple design and focus on gathering readily available information. Without additional resources to expand the project, improvements in EM-DAT's data quality and granularity will largely reflect the evolution of the global disaster information landscape, which has already contributed to gradual improvements in data completeness and accuracy [17,20]. Similarly, promising prospects for global disaster loss databases like EM-DAT lie in continued technological advancements and collaborative initiatives driven by international agendas.

At the international level, the SFDRR came as an opportunity to rethink the loss indicators monitoring systems and propose specific avenues to improve data on hazard-related loss and damage, emphasizing standardization, operationalization, and integration across global, regional, and local levels, with *ad hoc* support, and inclusion of all sectors [100,101], including collaboration across the reinsurance, humanitarian, and academic sectors [114,115]. While some standardization has been achieved among disaster loss databases over time [20,29,33,34], database managers face operational challenges limiting standard compliance capabilities [19,20]. From EM-DAT's perspective, compliance with current and future standards is feasible only with sufficient data sources, detail, and flexibility to align information with evolving operational standards and definitions. Still, EM-DAT has mostly access to bulk impact data from available sources, most of them having a global scope (Table 2). Supporting SFDRR indicators, the DesInventar Sendai database is independent of EM-DAT and relies on bottom-up data collection from member states, characterized by much lower entry criteria and higher spatial granularity. However, its spatiotemporal coverage remains uneven, limiting overall consistency and comparability [16,23]. Nonetheless, the SFDRR and the DesInventar Sendai database offer a federative framework potentially integrating multiple governance and management levels, with collaboration across humanitarian, reinsurance, and academic sectors instrumental for future improvements in disaster loss data.

On the technical side, further improving EM-DAT's spatiotemporal accuracy represents a practical development path. Precise timing and location enable effective interoperability between EM-DAT and external systems, whether bibliographic, climatic, geophysical, demographic, economic, public health databases, or other disaster loss databases (Section 4), to revise or complement the data, e.g., with exposure, vulnerability, or capacity indicators. In particular, increased coverage for mortality and public health data would pave the way for better standardization and evaluation of epidemic or heatwave data, as well as long-term monitoring of the health impact of disasters [26,100].

Artificial Intelligence (AI) could significantly enhance many of these processes by assisting with disaster event identification, impact data extraction from unstructured text, and pairing similar or overlapping events. Internally, AI integration within the data encoding system, alongside direct access to textual sources, could save time, particularly during database restructuring or new indicator incorporation. AI could similarly aid user queries and data analyses. Nonetheless, AI-based solutions for data collection require careful design to avoid amplifying existing biases in disaster loss databases (Section 5.1) or generating inadequately standardized and documented data.

6. Conclusion

This paper provides unprecedented transparency into the EM-DAT project's history, data collection processes, data sources, validation routines, and known limitations. Beyond serving as an authoritative reference and essential resource for an expanding global user base, it consolidates and documents a series of recent achievements aimed at improving EM-DAT's transparency and service quality. These include the transition to open access in 2020, which introduced a public download portal, the development of a refined database model with strengthened constraints and validation procedures, the release of a comprehensive online documentation portal in 2023, and the alignment with FAIR principles through the EM-DAT Archive associated with this manuscript.

EM-DAT has evolved significantly over its extensive history, currently encompassing more than 26,000 disaster entries spanning diverse regions, periods, and hazard types. However, intrinsic limitations and biases persist—particularly toward recent, highly impactful, and geographically well-reported events—due to inherent constraints in its passive collection methodology. Despite these limitations, EM-DAT remains one of the most comprehensive global disaster databases, and its data have proven valuable across many use cases. Importantly, these limitations also represent opportunities: EM-DAT entries can often be enriched and refined retrospectively by leveraging newer, complementary datasets, methodologies, and analytical tools. As demonstrated by recent applications, such integration facilitates more nuanced disaster risk analyses, filling some gaps left by historical biases or incomplete reporting. Ultimately, a key lesson from EM-DAT's development is that systematic documentation today provides an essential foundation for tomorrow's investigations. Even minimal disaster records, when properly maintained, can significantly enhance our understanding of global disaster risks over time.

However, merely preserving minimal documentation is insufficient. In an era where disaster risks are influenced by climate change and evolving societal contexts, proactive data collection of reliable and rigorously documented impact data remains crucial for advancing disaster risk science, informing evidence-based management strategies, and guiding policy decisions. These priorities are emphasized by the UN Sendai Framework for Disaster Risk Reduction 2015–2030. Since EM-DAT primarily relies on the passive collection of available online information, future improvements in data quality will depend on increased societal investment in systematic disaster impact monitoring and open reporting, scaling with new resources and technologies. Such efforts driven by global disaster risk reduction agendas and strengthened collaboration among stakeholders, including scientific communities and various sectors, will ultimately support a more accurate and comprehensive representation of disaster impacts worldwide.

6.1. Data, software, & code availability

This article refers to two primary data products: (i) the EM-DAT Living Dataset, updated weekly, available upon registration at https://public.emdat.be/ (custom terms of use), and documented at https://doc.emdat.be/, and (ii) the EM-DAT Archive [28] adhering to FAIR principles to encourage open and reproducible sciences while using the EM-DAT data, licensed under CC-BY-NC-ND. The EM-DAT Archive is technically validated with the EM-TEST framework [35] before publication. Readers are referred to the Data & metadata access section for more details. This article makes use of various Python software, including matplotlib, pybibliometrics, scipy, pandas, geopandas, pandera, and wordcloud [44,45,116–120], and other free tools for figure editing, including diagrams.net and Inkscape.

CRediT authorship contribution statement

Damien Delforge: Writing – review & editing, Writing – original draft, Visualization, Validation, Software, Investigation, Formal analysis, Data curation, Conceptualization. **Valentin Wathelet:** Writing – review & editing, Validation, Software, Data curation. **Regina Below:** Writing – review & editing, Validation, Project administration, Investigation, Data curation. **Cinzia Lanfredi Sofia:** Writing – review & editing, Investigation. **Margo Tonnelier:** Writing – review & editing, Data curation. **Joris A.F. van Loenhout:** Writing – review & editing, Supervision. **Niko Speybroeck:** Writing – review & editing, Supervision.

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Declaration of competing interest

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Data availability

Data accessibility, including data links, are described in the manuscript.

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