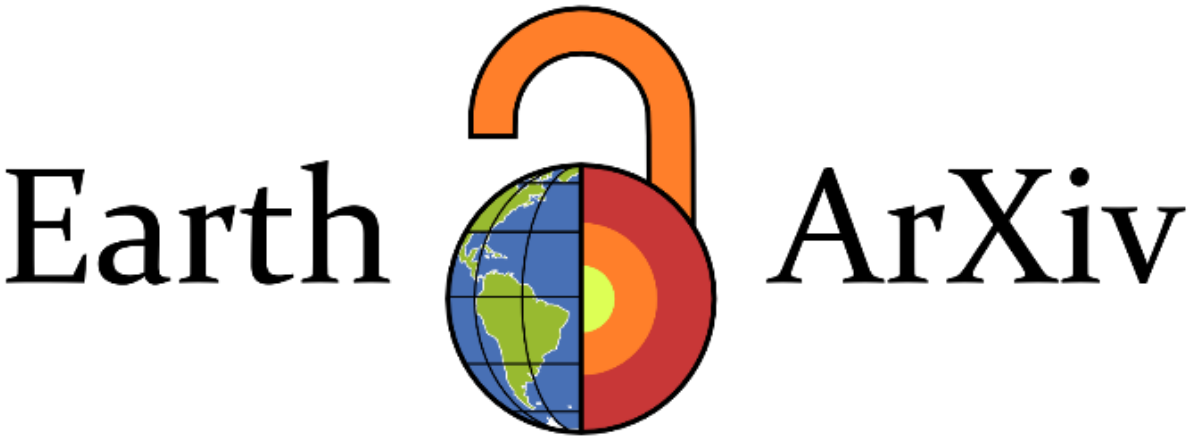


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Knowledge graph and dataset of global storms (1990–2023)

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Abstract

From 1990 to 2023, storms accounted for 45.3% of recorded disaster damage and 18.2% of disaster deaths. Yet impact records do not say how strong a storm was where it struck, who was exposed or why a value is missing. This knowledge graph and dataset cover storms of eleven subtypes recorded in the Emergency Events Database from 1990 to 2023, in 1,595 country-years and 3,492 storm-country records. For those records with administrative units from Geo-Disasters, we extracted hazard (e.g., wind speed, precipitation), exposure (e.g., population density) and vulnerability (e.g., Human Development Index) measures suited to each subtype over the storm's affected administrative units and days from multiple sources including national and government indicators, an atmospheric reanalysis and the Google Earth Engine. Displacement records of the Internal Displacement Monitoring Centre and appeals of the International Federation of Red Cross and Red Crescent Societies are matched to storms. Cascades link storms to disasters that struck the same area within 91 days. Every method, from the modelled wind fields to the cascade links, follows a published study, with few minor stated deviations. The data are released as a Resource Description Framework knowledge graph linked to Wikidata and as tables of comma-separated values. The tables load

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into a SQLite database with the primary and foreign keys given in the schema.

Keywords: tropical cyclones, EM-DAT, disaster impacts, reanalysis, missing data, linked data, Google Earth Engine

Specifications Table

Subject	Earth and Planetary Sciences
Specific subject area	Storm hazards and their human and economic impacts, from global disaster records, atmospheric reconstrunctions and gridded exposure.
Type of data	Resource Description Framework knowledge graph (Turtle), tables of comma-separated values
Data collection	Storm records were exported on 1 October 2026 from the Emergency Events Database (EM-DAT) and located with Geo-Disasters' administrative units. Hazard and exposure measures were read over each storm's administrative units and days. In Google Earth Engine, they were read from the Fifth Generation reanalysis of the European Centre for Medium-Range Weather Forecasts and its land component, the Modern-Era Retrospective analysis for Research and Applications, Version 2 (MERRA-2), the Gridded Population of the World, version 4, the Global Human Settlement Layer, the Shuttle Radar Topography Mission and the WorldCover map of the European Space Agency. Storm tracks were read from the International Best Track Archive for Climate Stewardship, with wind fields modelled on the CLIMate ADAptation platform. Storm surge was read from the Global Tide and Surge Model v3, through the Copernicus Climate Data Store. Records of the Internal Displacement Monitoring Centre (IDMC) and of the International Federation of Red Cross and Red Crescent Societies (IFRC) were matched to storms by GLobal IDEntifier number and dates.
Data source location	Centre for Research on the Epidemiology of Disasters (CRED, UCLouvain, Belgium), National Centers for Environmental Information of the National Oceanic and Atmospheric Administration (USA), European Centre for Medium-Range Weather Forecasts / Copernicus, Global Modeling and Assimilation Office of the National Aeronautics and Space Administration (USA), Deltares, IDMC, IFRC, United Nations Development Programme, World Bank
Data accessibility	Repository name: Zenodo. Data identification number: 10.5281/zenodo.24077003. Licence: Creative Commons Attribution 4.0 International. Direct URL to data: `https://doi.org/10.5281/zenodo.24077003`. Code: Zenodo, `https://doi.org/10.5281/zenodo.24078897` [1], developed at `https://github.com/ridwanmonjur/github_dataset_storms`. Licence: GNU General Public License v3.0. EM-DAT's values are not redistributed but readers and reviewers can obtain them from CRED at `https://public.emdat.be`. Our code rebuilds the full dataset from that export.
Related research article	—

1. Value of the Data

- Each storm-country record holds every impact its sources report. These are the deaths, injured, affected, homeless, total affected and economic damage of the Emergency Events Database (EM-DAT). They also include the new internal displacements of the Internal Displacement Monitoring Centre (IDMC) and the amounts requested and funded by appeals of the International Federation of Red Cross and Red Crescent Societies (IFRC).

- Each storm has the hazard measures its subtype needs to explain these impacts. EM-DAT has 11 storm subtypes with distinct characteristics, and each has its own hazard.

- Each storm's impacts also depend on the exposure of its area and the vulnerability of its country. Exposure includes the population, built-up surface and mean elevation of the area whilst vulnerability is given by national and government indicators.

- Every value is annotated. Each link states how certain it is, and each hazard and exposure value has a status that says why it is present or absent: `not_applicable` where the measure does not describe the subtype, such as surge for a tornado or convection for a blizzard, `not_covered` where the product does not reach the place or time, and `not_recorded` where the source is silent. A blank is therefore never a zero, and users can retain only the links and values at the confidence they need.

- Compound and cascading impacts can be studied by following each storm to the floods, landslides and other disasters that struck the same area within 91 days.

- In the graph, one query can follow a storm through chains of later disasters in the same area and join each country to Wikidata, without joining tables.

2. Background

Disaster databases such as EM-DAT [2] record the deaths, people affected and damage of each event in each country. They do not record how strong a storm was where it struck, the population exposed or why a value is missing. Jones et al. [3] found that their gaps followed year, income and disaster type. Hazard measures from physical datasets avoid these reporting biases.

In the risk framework of the Intergovernmental Panel on Climate Change [4], impacts depend on hazard, exposure and vulnerability, so explaining them requires all three beside the impact records. Studies of storms showed each component at work. Bakkensen and Mendelsohn [5] found that cyclone damage and deaths rose with intensity where the storm struck and fell with national income. Klawa and Ulbrich [6] related windstorm losses to the wind above its local extremes. Taszarek et al. [7] found that severe thunderstorms formed where instability and wind shear combined. Taszarek et al. [8] found that the convective parameters of the Fifth Generation reanalysis of the European Centre for Medium-Range Weather Forecasts (ERA5) agreed with rawinsonde observations.

MacManus et al. [9] mapped the populations concentrated in the low elevation coastal zone, where coastal storms strike. Mester et al. [10] linked displacement, deaths and damage to observed flood hazard in a flood displacement dataset but left storms to future work. Jäger et al. [11] found that hazards following one another in the same area accounted for most recorded damage and deaths. Following these studies, this dataset integrates, for every storm subtype, the hazard, exposure, vulnerability and cascade context that can shape a storm's impacts in one knowledge graph (KG). In a KG [12], an event, country or track is one node however many sources describe it, and cascades are edges between events that a query can follow through any number of steps. Its countries link to Wikidata [13], so the data join other linked data, which makes them interoperable and reusable as the FAIR principles ask [14]. KnowWhereGraph [15] links hazards, demographics and other data in a KG through regions; this KG links the records of each storm through the event.

3. Data Description

The deposit [16] holds the same records in two forms: tables of comma-separated values and a Resource Description Framework (RDF) KG, as well as the files that describe them. Seventeen tables are classes of the graph, in which each row is a node, each column a property and each key an edge.

3.1. Coverage

Every hazard and exposure value has a status column and, when empty, a gap column that gives the reason. An empty value therefore means unknown and is never read as zero. Because the eleven subtypes share the tables, a measure is marked `not_applicable` for every subtype it does not describe: a tornado has no surge or wave values, and a blizzard no convection values. Table 1 gives the storm-country records by subtype and the share that report each impact.

Table 1: Storm-country records of 1990–2023 by subtype, and share with each impact reported.

Subtype	Records	With area	Deaths	Affected	Damage	Homeless	Injured
Tropical cyclone	1,754	1,448	0.76	0.79	0.60	0.18	0.33
Storm (general)	563	419	0.72	0.65	0.43	0.17	0.32
Severe weather	248	197	0.66	0.65	0.38	0.10	0.31
Tornado	239	216	0.75	0.82	0.59	0.29	0.68
Blizzard / winter storm	206	177	0.80	0.42	0.47	0.04	0.23
Lightning/thunder-storms	180	174	0.77	0.64	0.52	0.13	0.37
Extra-tropical storm	177	107	0.68	0.29	0.49	0.01	0.16
Hail	91	77	0.52	0.73	0.54	0.18	0.46
Sand/dust storm	20	19	0.75	0.75	0.35	0.00	0.60
Storm surge	8	7	0.88	0.88	0.12	0.12	0.50
Derecho	6	5	0.67	0.50	0.67	0.00	0.33
All storms	**3,492**	**2,846**	**0.74**	**0.70**	**0.54**	**0.16**	**0.34**

Every subtype reads `weather_features.csv` (class EventWeather) and `exposure_features.csv` (class EventExposure), and each reads the other hazard tables according to what its impacts depend on (Table 2).

Table 2: Hazard and exposure tables, with their class, their content, the storm subtypes each is read for and the records read, tables read for the same subtypes together.

Table	Class	Content	Subtypes read	Records
`weather_features`	EventWeather	Pressure, rain, wind, temperature and the loss index over the window	All	2,846
`exposure_features`	EventExposure	Population, built-up surface and mean elevation of the area		
`lecz_below_10m_share`	EventExposure	Share of the area in the low elevation coastal zone	Tropical cyclone, storm surge, storm (general), extra-tropical storm	1,981
`gtsm_features`	EventStorm Surge	Modelled storm surge, its day and the total water level		
`wave_features`	EventWaves	Significant wave height		

Table	Class	Content	Subtypes read	Records
`track_features`	EventTrack Intensity	Matched best track, its intensity at the closest point and its modelled wind over the area	Tropical cyclone, storm surge, storm (general)	1,874
`convection_features`	Event Convection	Instability, wind shear, updraft speed, convective rain and rain rate	Tornado, hail, lightning/thunder-storms, severe weather, derecho, storm (general)	1,088
`snow_features`	EventSnow	Snowfall and snow depth	Blizzard / winter storm	177
`dust_features`	EventDust	Dust surface concentration and dust optical depth	Sand/dust storm	19

3.2. Knowledge graph

A KG stores data as nodes joined by directed, labelled edges. In RDF, each edge is a triple of subject, predicate and object. The graph is gzipped Turtle, written one triple per line as N-Triples, which any RDF store or library loads, such as Oxigraph, GraphDB or rdflib, and which can be streamed or split by line without one. The graph has two kinds of node, entity nodes and row nodes.

An entity node stands for an event, country or IBTrACS track: each is one node, however many tables mention it. A query names the event or country once and reaches every record about it, without the keys of each table. A row node stands for a row of a table and is typed by the table's class. Each source row stays one node with its own values, status and gap, so no record is merged with another or filled in. Each of its values is a property with its unit, so a query can compare values without the data dictionary. Dates are typed, and coordinates are typed as geographic points.

Table 3 gives every class with its source, its nodes and its content, and Fig. 1 places every class under one of eight main classes.

Table 3: Classes of the knowledge graph by main class, with their source, their nodes in the deposited graph and their content.

Main class	Class	Source	Content	Nodes
Event	Storm	EM-DAT	A storm, joined to its countries, its track and the disasters it influenced	3,270
Entity	Country	Wikidata	A country, the same as its Wikidata item	190
	Track	IBTrACS	A best track matched to a storm	565
SourceRecord	AffectedUnit	Geo-Disasters	GAUL units struck by the storms and their cascade partners	19,800
	TrackPoint	IBTrACS	Points of the 565 tracks matched to storms	44,672
	Displacement Record	IDMC	Displacement rows matched to a storm, with method and confidence	1,315
	AidAppeal	IFRC GO	Appeals matched to a storm, with method and confidence	262
	DisasterRecord	EM-DAT	EM-DAT's rows, only in the graph built from the user's own export	—
Location	EventLocation	EM-DAT, Geo-Disasters	Every storm-country record: its coordinate, its event area and grade	3,492
Hazard	EventTrack Intensity	IBTrACS [17], CLIMADA	Matched track, its intensity, radii and motion at the closest point and its modelled wind over the area	2,846
	EventWeather	ERA5 [18]	Pressure, rain, wind, temperature, loss index	2,846
	EventConvection	ERA5	CAPE, shear, total totals index, WMAXSHEAR, convective rain, rain rate	2,846
	EventWaves	ERA5	Significant wave height	2,846
	EventStormSurge	GTSM v3	Surge and its day, total water level, stations	2,846
	EventSnow	ERA5, ERA5-Land [19]	Snowfall, snow depth	2,846
	EventDust	MERRA-2 [20]	Dust surface concentration, dust optical depth	2,846

Main class	Class	Source	Content	Nodes
Exposure	EventExposure	GPWv4 [21], GHSL, SRTM, LECZ v3	Population, built-up surface, elevation, LECZ share	2,846
Vulnerability	Human Development	UNDP	HDI of the country-years with a storm	1,546
	Economy	World Bank WDI	GDP per capita, population	1,546
	Governance	World Bank WGI	Government effectiveness	1,547
Cascade	EventCascade	EM-DAT, Geo-Disasters	Influences between records: overlap, lag, confidence	2,505
All				**103,478**

Abbreviations: CAPE = convective available potential energy; CLIMADA = CLIMate ADAptation platform; EM-DAT = Emergency Events Database; ERA5 = Fifth Generation reanalysis of the European Centre for Medium-Range Weather Forecasts; ERA5-Land = land component of ERA5; GAUL = Global Administrative Unit Layers; GDP = gross domestic product; GHSL = Global Human Settlement Layer; GPWv4 = Gridded Population of the World, version 4; GTSM = Global Tide and Surge Model; HDI = Human Development Index; IBTrACS = International Best Track Archive for Climate Stewardship; IDMC = Internal Displacement Monitoring Centre; IFRC = International Federation of Red Cross and Red Crescent Societies; LECZ = low elevation coastal zone; MERRA-2 = Modern-Era Retrospective analysis for Research and Applications, Version 2; SRTM = Shuttle Radar Topography Mission; UNDP = United Nations Development Programme; WDI = World Development Indicators; WGI = Worldwide Governance Indicators; WMAXSHEAR = updraft speed from CAPE times bulk shear.

Table 4 and Fig. 2b show the edges, which join a row node to the entities its keys name, and entities to each other. From a storm, a query thus reaches its records, its countries, its track and the disasters it influenced without using the table keys, and from a country its Wikidata item. The full graph holds 2,103,546 triples, and the deposited graph without EM-DAT's values 1,958,768.

Table 4: Edges of the knowledge graph, with the classes they join and their number in the deposited graph.

Edge	From → to	Edges	Meaning
`event`	Row → Event	47,637	The event a row is about
`country`	Row → Country	54,781	The country of a row
`track`	TrackPoint, EventTrackIntensity → Track	45,432	The IBTrACS track of a point or of a matched record

Edge	From → to	Edges	Meaning
`fromEvent`, `toEvent`	EventCascade → Event	2,505 each	The two events of a cascade
`hitCountry`	Event → Country	3,492	A storm struck the country
`matchedTrack`	Event → Track	605	The IBTrACS track matched to a storm
`influences`	Event → Event	2,437	The event influenced a later one in the same area
`owl:sameAs`	Country → Wikidata item	188	The same country in Wikidata
Value properties	Row → value	1,450,361	One per value, with its unit in the vocabulary, of which 117,332 are statuses that state why a value is present or absent

Abbreviations: IBTrACS = International Best Track Archive for Climate Stewardship; owl = prefix of the Web Ontology Language.

Fig. 2 follows one record, Typhoon Haiyan in the Philippines, from its table row to its node and on to a query. In the tables (Fig. 2a), the record is one row of `track_features.csv`. The row is keyed by `disasterno` and `iso3`, names its matched track in `track_sid` and gives the wind at the closest point, 155 knots, with its status.

In the graph (Fig. 2b), the same row becomes a node of class EventTrackIntensity. Its three keys become edges to the storm, the country and the track. The query in Fig. 2c starts from the track's name and follows the `influences` edges through any number of steps, through floods and landslides, to the storms that followed Haiyan in the same areas. It returns their countries with their Wikidata items and reads each country's population live from Wikidata, without using a table key. In tables, the same chains need a recursive join, and the population a second source.

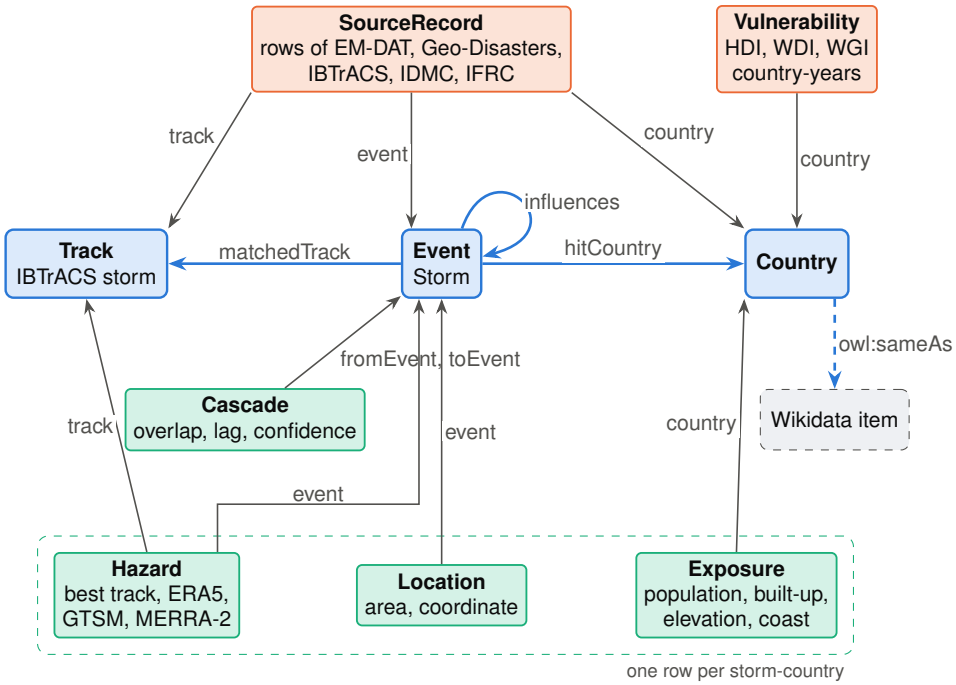


Figure 1: Main classes of the knowledge graph and the edges between them. Entities (blue) are the hubs: events, countries linked to Wikidata and tracks. Source rows are orange, and the storm-country records built for this dataset green. Table 3 lists the classes under each main class. *Abbreviations:* EM-DAT = Emergency Events Database; ERA5 = Fifth Generation reanalysis of the European Centre for Medium-Range Weather Forecasts; GTSM = Global Tide and Surge Model; HDI = Human Development Index; IBTrACS = International Best Track Archive for Climate Stewardship; IDMC = Internal Displacement Monitoring Centre; IFRC = International Federation of Red Cross and Red Crescent Societies; MERRA-2 = Modern-Era Retrospective analysis for Research and Applications, Version 2; owl = prefix of the Web Ontology Language; WDI = World Development Indicators; WGI = Worldwide Governance Indicators.

(a) A row of `track_features.csv` (five of its columns)

```
disasterno,iso3,track_sid,track_closest_wind_kt,track_closest_wind_kt_status
2013-0433,PHL,2013306N07162,155.0,reported
```

(b) The same row in the graph, with the entities its keys name (Turtle, abridged)

```
@base <https://w3id.org/storms/> .
@prefix v: <https://w3id.org/storms/vocab/> .
@prefix unit: <http://qudt.org/vocab/unit/> .
<track_features/2013-0433/PHL> a v:EventTrackIntensity ;
    v:event <event/2013-0433> ; v:country <country/PHL> ;
    v:track <track/2013306N07162> ;
    <vocab/track_features/track_closest_wind_kt> 155.0 ;
    <vocab/track_features/track_closest_wind_kt_status> "reported" .
<event/2013-0433> a v:Event, v:Storm ;
    v:matchedTrack <track/2013306N07162> ;
    v:hitCountry <country/PHL>, <country/VNM>, <country/CHN>, <country/PLW> ;
    v:influences <event/2013-0554>, <event/2014-0085> .
<country/PHL> owl:sameAs <http://www.wikidata.org/entity/Q928> .
<vocab/track_features/track_closest_wind_kt> qudt:unit unit:KN .
```

(c) `query1.rq`: the storms that followed Typhoon Haiyan through chains of influence, by country with its Wikidata item and its population read live from Wikidata, and its answer

```
SELECT ?country ?wikidata (COUNT(DISTINCT ?later) AS ?storms)
       (MAX(?pop) AS ?population) WHERE {
  ?t rdfs:label "HAIYAN 2013" .
  ?x a v:EventTrackIntensity ; v:track ?t ; v:event ?e .
  ?e v:influences+ ?later .
  ?later a v:Storm ; v:hitCountry ?c .
  ?c rdfs:label ?country ; owl:sameAs ?wikidata .
  SERVICE <https://query.wikidata.org/sparql> {
    ?wikidata wdt:P298 ?iso3 ; wdt:P1082 ?pop } }
GROUP BY ?country ?wikidata ORDER BY DESC(?storms)
```

```
CHN wd:Q148 14 1,404,890,000 | PHL wd:Q928 4 112,729,484
TWN wd:Q865 2 23,317,031     | VNM wd:Q881 2 96,208,984
```

Figure 2: Typhoon Haiyan in the Philippines (EM-DAT 2013-0433, PHL) in the tables (a), in the graph (b) and in a competency question with its answer (c). Country codes (ISO 3166-1 alpha-3): CHN = China; PHL = Philippines; PLW = Palau; TWN = Taiwan (Province of China); VNM = Viet Nam. *Abbreviations:* EM-DAT = Emergency Events Database; IBTrACS = International Best Track Archive for Climate Stewardship; ISO = International Organization for Standardization; KN = knot, the unit code of the qudt vocabulary; kt = knots (in column names); owl = prefix of the Web Ontology Language; qudt = prefix of the Quantities, Units, Dimensions and Types vocabulary; rdfs = prefix of the Resource Description Framework Schema; sid = IBTrACS storm identifier; P1082 = population and P298 = ISO 3166-1 alpha-3 code, Wikidata properties (P298 keeps the request to countries); v = prefix of this dataset's vocabulary; wd = prefix of Wikidata items; wdt = prefix of Wikidata's direct properties.

3.3. Files

Table 5 lists every file of the deposit by purpose.

Table 5: Files of the deposit by purpose, with their rows or triples.

Purpose	Files	Count
KG	`storms_public.ttl.gz`, with its vocabulary (`storms_public_vocab.ttl`) and SHACL shapes (`storms_public_shapes.ttl`), and the SPARQL competency questions `query1.rq`–`query6.rq`	1,958,768 triples
Impacts	`idmc.csv`, `ifrc.csv`	1,577 rows
Hazard	`track_features.csv`, `weather_features.csv`, `convection_features.csv`, `wave_features.csv`, `gtsm_features.csv`, `snow_features.csv`, `dust_features.csv`	19,922 rows
Exposure	`exposure_features.csv`	2,846 rows
Vulnerability	`hdi.csv`, `wdi.csv`, `wgi.csv`	4,639 rows
Location and cascades	`event_points.csv`, `cascades.csv`, `geodisasters.csv`, `track_points.csv`	70,469 rows
Description	`data_dictionary.csv`, `schema.yaml`, `supplementary_information.pdf`	—

Abbreviations: KG = knowledge graph; SHACL = Shapes Constraint Language; SPARQL = SPARQL Protocol and Resource Description Framework Query Language.

The deposit holds seventeen tables of comma-separated values, each one class of Table 3. The event points are the table to which the others join and give each storm-country record its coordinate, event area and grade. The Geo-Disasters administrative units and the track points of IBTrACS retain the source rows from which the areas and tracks are built.

3.4. Rows and keys

The schema declaration file, `schema.yaml`, lists the primary and foreign keys of every table, so it alone shows how the tables join. Storm-country records are keyed by `disasterno` and `iso3`, country-years by `iso3` and `year`, and track points by `sid` and `time`. Geo-Disasters administrative units and IDMC rows have no key of their own, but each names its storm by `disasterno` and `iso3`. The same two columns join the deposited tables to the user's own EM-DAT export.

The code [1] loads the tables into a SQLite database. Each file of comma-separated values becomes one table with its column types and keys. SQLite's

foreign-key check confirms that every key points to a row. The database is not deposited, because it holds EM-DAT's values.

4. Experimental Design, Materials and Methods

4.1. Workflow, downloads and cleaning

Fig. 3 shows the five steps in which we built the dataset.

In step 1 (`run1_download_datasets.py`), we downloaded each source's raw file once, in one of three ways. Seven sources came through an application programming interface. The World Bank's served the World Development and Worldwide Governance Indicators, the Humanitarian Data Exchange's served IDMC, and IFRC GO served IFRC. Zenodo's served Geo-Disasters, the Earthdata interface of the National Aeronautics and Space Administration served the coastal zone grid, and Wikidata's query service served the countries' links. The Human Development Index and IBTrACS were scraped from their providers' websites, from which they can also be downloaded by hand. EM-DAT, which requires registration, was exported by hand.

In step 2 (`run2_clean_datasets.py`), we cleaned each source by one specification. We kept only the columns the dataset uses and renamed the keys to one name in every source (`disasterno`, `iso3`, `year`). Numbers and dates were typed, and counts and amounts were made non-negative. Rows dated outside 1990–2023 were dropped, and the country indicators were expanded to every country and year. The step also wrote each storm-country record's coordinate to `event_points.csv`.

Sections 4.2, 4.3 and 4.4 give the remaining steps 3, 4 and 5. The code [1] runs in Python 3.12, with versions pinned by uv, the Python package manager. The tables and areas use pandas 3.0, GeoPandas 1.2 and Shapely 2.2. The extracts use the Earth Engine Python application programming interface 1.7 and xarray, and the storm tracks use the CLIMate ADAptation platform 6.1. The graph uses rdflib 7.6, pySHACL 0.40 and Oxigraph 0.5, and the database uses SQLite.

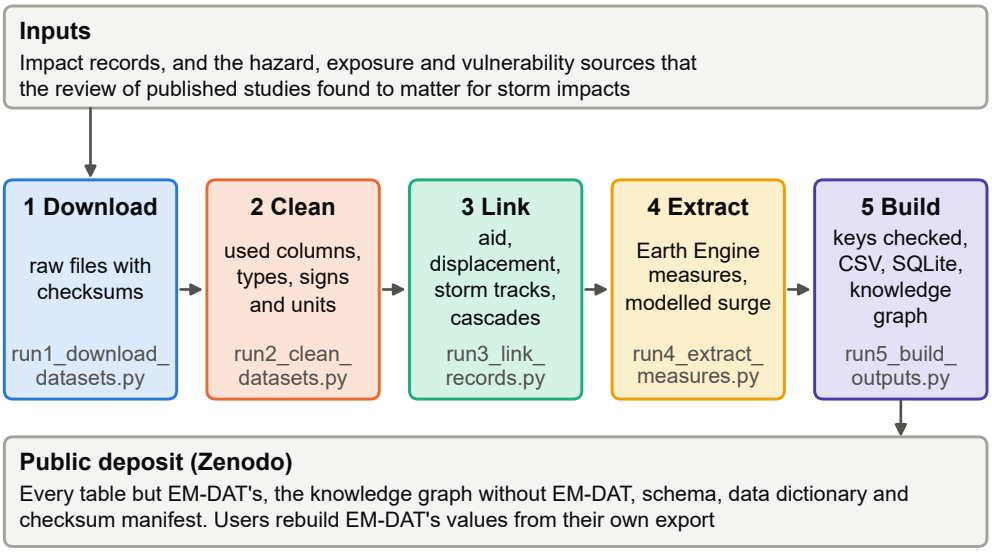


Figure 3: Workflow from the inputs to the public deposit. *Abbreviations:* CSV = comma-separated values; EM-DAT = Emergency Events Database.

4.2. Linking records to storms

In step 3 (`run3_link_records.py`), we gave each storm record its event area and linked it to the IBTrACS tracks, the IDMC displacements, the IFRC appeals and the cascades with other disasters.

4.2.1. Event area and coordinate

Following Teber et al. [22], the event area was the provinces or districts that Geo-Disasters lists as struck by the storm in the country. These first- or second-level administrative units are where EM-DAT reported the storm's impacts. Each administrative unit was graded 1 (EM-DAT's Global Administrative Unit Layers identifier), 2 (a GeoNames place matching such a unit), 3 (a match by province name) or 4 (GeoNames only). We dissolved the administrative units into one area per record and, as our addition, graded it by its weakest unit, because an area is only as reliable as its least certain unit. The record's coordinate was placed inside the largest part of its largest administrative unit. The two records with only an EM-DAT point, and administrative units across the date line, were read over a circle of 50 km or of the unit's equal-area radius. The circle shrank in 10 km steps until the European Space Agency's WorldCover showed land over half of it. Areas were geodesic, and no place name was geocoded.

Each record states in the status column `coord_status` whether it has a coor-

dinate, `reported` for 2,846 records and `not_recorded` for the 646 without one. Each area takes the weakest grade of its administrative units in the column `area_quality`, which is empty for a circle.

4.2.2. Storm tracks

Following Eberenz et al. [23], we matched tropical cyclones, storm surges and general storms with the CLIMate ADAptation platform to IBTrACS best tracks, the tracks agencies re-analyse after the season from every observation. A track was a candidate when its wind field reached 17.5 m/s over the event area and it began 0 to Δt days before every possible EM-DAT start day. The window pairs (Δt_1, Δt_2) were (10, 50), (15, 50), (25, 50), (10, 25) and (15, 25) days, tried in this order as levels 1 to 5. A track was assigned at the first level where it was the only candidate in both windows and not yet assigned in that country.

Each assigned track is graded in the confidence column `track_confidence` by the level at which it was assigned.

Each of the eight track values has a gap and a status column, such as `track_wind_kt_gap` and `track_wind_kt_status`. The gap `not_applicable`, for the eight other subtypes, gives the status `not_applicable`, `no_track_match` gives `not_covered`, and `ambiguous_track` or `no_event_date` give `not_recorded`. A value blank in IBTrACS is `not_recorded` without a gap, a 0 is `zero`, and any other value is `reported`.

4.2.3. Displacement and appeals

Following Mester et al. [10], we matched each IDMC row and IFRC appeal of a storm hazard type to the closest storm of its country starting at most 30 days apart. As our addition, a GLobal IDEntifier (GLIDE) number matched first. Rows dated only to the month or year stayed unmatched. IDMC covers 2008–2023 and IFRC 1990–2023, so a record without matched rows in those years has none in the source. Each match is graded in a confidence column, `idmc_confidence` in `idmc.csv` and `ifrc_confidence` in `ifrc.csv`. The grade follows the match, by GLIDE number, by date, or by date to a storm dated only to its month.

4.2.4. Cascades

Jäger et al. [11] built their cascade rule for every natural hazard type of EM-DAT with an area (storms, floods, earthquakes, droughts, extreme temperatures, wet and dry mass movements and volcanic activity), so the storms are linked to disasters of every type by the same rule. Following them, an EM-DAT record influenced another in the same country when their areas overlapped by at least 50%,

measured as the larger of the two shares. Their start dates also had to be at most 91 days apart, with the influencing record first and a tie counting both ways. As in their code, areas were compared in Web Mercator and a missing start day was read as the 1st of the month, which `date_precision` marks. We retained only links with a storm at one end. Each cascade is graded in the confidence column `confidence` by whether EM-DAT lists the partner's type among the storm's associated hazards. Where it does not, the grade follows whether both start dates are known to the day.

4.3. Extracting hazard and exposure from physical datasets

In step 4 (`run4_extract_measures.py`), we extracted the hazard and exposure measures over each storm's event area (Section 4.2) and window. The window ran from one day before EM-DAT's start date to one day after its end date, for at most 14 days, or over the start month when the start day was unknown. Earth Engine filled six tables, each with one row per record with an event area and its own class in the KG. Table 2 gives the subtypes for which each table is read.

Each measured value has a gap column, which states why it is empty, and a status column derived from it, such as `era5_wind_max_ms_gap` and `era5_wind_max_ms_status`. The status is `not_applicable` for a subtype the measure does not describe (the layers each subtype reads are fixed in the code, and every other layer is marked so rather than left blank), and `not_covered` where the product does not reach the place or time. The gaps behind `not_covered` are `outside_coverage`, `coord_off_land`, `no_land_cell`, `no_sea_cell`, `no_coastal_station` and `not_yet_available`. The status is `not_recorded` where the read failed (`error`), returned nothing (`no_data`) or lacked a start date (`no_event_date`), or where a value is blank without a gap. Otherwise it is `not_extracted` for a row not yet read, `zero` for a 0 and `reported` for any other value.

Each measure's raw values are stored in their own units, and Table 6 states how each measure is computed. The supplementary information gives the product, band and reduction of every column and the formulas of values users can compute, such as population density. Each method follows its published study, and the table states the two points where we departed from it.

Table 6: Each method as applied, with its departures from the published study.

Method (study)	As applied
Every gridded value	Read on the product's own grid in Google Earth Engine, with partly covered cells weighted by their covered fraction. Totals are area means, peaks are area maxima, and pressure and cold are area minima
Population [10]	Zonal sum of GPWv4
Loss index [6]	Klawa and Ulbrich's Eq. 2, $LI = \sum_c P_c \sum_d \max\left(v_{c,d}/v_{98,c} - 1,\ 0\right)^3$. Here P_c is the GPWv4 population of cell c, $v_{c,d}$ its ERA5 10 m maximum wind on day d, and $v_{98,c}$ its 98th percentile over 1991–2020
Cyclone intensity [5]	IBTrACS wind, pressure and category at the track point closest to the area, beside the matched track's Holland wind field from CLIMADA
WMAXSHEAR [7]	$\sqrt{(2 \cdot \text{CAPE})} \times$ bulk shear, with most-unstable CAPE. *Departure:* the shear runs from 10 m to 500 hPa instead of 0–6 km, because Earth Engine holds no model levels
Surge, total water level [24]	GTSM v3 daily maxima at the coastal stations. *Departure:* surge is read at the stations within the area's radius plus 50 km
Coastal zone [9]	Share of the area's land at or below 10 m connected to the coast, from the LECZ v3 grid

Abbreviations: CAPE = convective available potential energy; CLIMADA = CLIMate ADAptation platform; ERA5 = Fifth Generation reanalysis of the European Centre for Medium-Range Weather Forecasts; GPWv4 = Gridded Population of the World, version 4; GTSM = Global Tide and Surge Model; IBTrACS = International Best Track Archive for Climate Stewardship; LECZ = low elevation coastal zone; LI = loss index; WMAXSHEAR = updraft speed from CAPE times bulk shear.

4.4. Building and checking the dataset

In step 5 (`run5_build_outputs.py`), we built the SQLite database from the tables with the primary and foreign keys given in `schema.yaml`, and SQLite verified that every primary key was unique and every foreign key pointed at a row. From the same tables, the step built the KG (Section 3.2), and the whole graph conformed to its Shapes Constraint Language shapes. It then wrote the deposit without EM-DAT's values. Three tests against independent records were written to assess the links and values. The assigned IBTrACS name agreed with EM-DAT's storm name for 95.9% of 728 records (level 3: 42.9%). Of 216 IDMC rows matched by GLIDE, 90.7% fall on the same storm when matched by dates alone. ERA5 underestimates cyclone wind, as Dulac et al. [25] found: its strongest wind over the area is a median 0.54 of the storm-track wind, and 0.36 in categories 4–5.

Limitations

The dataset inherits the limitations of the datasets and studies it builds on. EM-DAT omits storms below its entry thresholds and leaves many impacts unreported, and Jones et al. [3] found that its gaps follow year, income and disaster type. Geo-Disasters locates some administrative units by place name only, ERA5 underestimates cyclone intensity [25], and the Global Tide and Surge Model underestimates surge under cyclones [24]. IDMC records displacement only from 2008, and the vulnerability indicators describe whole countries rather than the event area. All of these sources and methods passed peer review, and the 18 cited works had a median of 219 citations in OpenAlex in November 2026. Their citations ranged from 9 to 33,725, with a mean of 2,944.

The steps that built this dataset add limitations of their own. The tracks, displacement rows, appeals and cascades were linked by automatic matching rules. We verified 200 of these links by hand and the rest by analysis in Python, not record by record. EM-DAT's values are not in the deposit and are rebuilt from the user's own export [terms to be confirmed with the Centre for Research on the Epidemiology of Disasters].

Ethics Statement

The authors have read and followed the ethical requirements for publication in Data in Brief. The work involves no human subjects, animal experiments or data collected from social media platforms. EM-DAT data were used under the terms of use of the Centre for Research on the Epidemiology of Disasters and are not redistributed.

Data Availability

A knowledge graph and dataset of global storms for impact prediction, 1990–2023 (Original data) (Zenodo) https://doi.org/10.5281/zenodo.24077003, Creative Commons Attribution 4.0 International.

Processing code for the knowledge graph and dataset of global storms (Software) (Zenodo) https://doi.org/10.5281/zenodo.24078897, GNU General Public License v3.0.

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Declaration of Competing Interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

Declaration of generative AI and AI-assisted technologies in the manuscript preparation process

During the preparation of this work the authors used Claude Opus 5.5 (Anthropic) to draft and revise the text. After using this tool, the authors reviewed and edited the content as needed and take full responsibility for the content of the publication.

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