Evaluating reliability and limitations of disaster loss accounting databases

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Abstract
Disaster loss accounting is an essential tool for assessing the effects of disasters and creating policies for disaster risk reduction that are supported by data. This study compares disaster data for two of the most used disaster loss accounting databases, EM-DAT and DesInventar in the context of six Latin American countries, namely, Uruguay, Chile, Costa Rica, Nicaragua, Honduras, and Venezuela. The analysis focuses on the quantitative reporting differences for corresponding indicators and disaster events. In their current state, disaster loss accounting databases have several flaws, including a limited use of Global Identifier Numbers (GLIDE), a general description of their sources, a large number of missing data, a lack of a common terminology, an underrepresentation of slow-onset hazards and low-intensity disasters, and insufficient reporting of secondary disasters. However, these restrictions should not be seen as a reason to cease utilizing the databases, but rather as a motivation to enhance them and use them at their full potential.

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Summary

Disaster loss accounting databases have great potential in improving risk assessment, preparedness, and management processes. They can give inputs in calculating needs, feasibility of project investments and in supporting policies aimed at reducing disaster risk. Their importance is also recognized by the 2015 Sendai Framework. In Priority for Action1 it advocates for the use of space-based risk information and the promotion of real time access to reliable data. Nevertheless, even the use of these databases can provide several advantages, they are far from being perfect.

In this study two of the most used disaster loss accounting databases, EM-DAT and DesInventar have been analysed by looking at their reliability in measuring the impact of disaster events and at their limitations. This has been done by comparing disaster data for six Latin American countries: Uruguay, Chile, Costa Rica, Nicaragua, Honduras, and Venezuela, for an established set of natural events and human centred indicators. Disaster events common across the two databases have been hand-matched and studied using graphic representations and percentages of commonalities and discrepancies. All entries where the events could not be matched due to missing data were left out of the analysis.

Both databases are very comprehensive in terms of disaster categories and temporal frame, but also present several inconsistencies. It is often the case that for the same disaster event and indicator, EM-DAT and DesInventar report different data. This decreases their reliability making it challenging to determine which one provides the most accurate estimations.
The existing state of disaster loss accounting databases is far from ideal and comes with various limitations. These limitations include inadequate utilization of GLIDE numbers, vague descriptions of data sources, extensive amounts of missing data, lack of a standardized terminology, insufficient representation of slow onset hazards and low intensity disasters, and inadequate reporting of secondary disasters. However, instead of abandoning the use of these databases, these limitations should be seen as an opportunity for improvement and a reason to utilize them to their fullest potential.

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List of Acronyms

CRED	Centre for Research on the Epidemiology of Disasters
EM-DAT	Emergency Events Database
GDP	Gross Domestic Product
GLIDE	Global Unique Disaster Identifier number
NGO	Non-Governmental Organisation
OCHA	United Nations Office for the Coordination of Humanitarian Affairs
SFDRR	Sendai Framework for Disaster Risk Reduction
UNDP	United Nations Development Programme
UNDRR	United Nations Office for Disaster Risk Reduction
UNFCCC	United Nations Framework Convention on Climate Change
WHO	The World Health Organization

1. Introduction

1.1 Background and motivation

Risk assessment, preparedness, and management processes require a systematic collection of reliable and comparable data on disaster damage and loss (European Commission, 2013). It has been acknowledged that implementing data solutions at national, provincial, and local levels is a crucial first step in strengthening the capacities of relevant stakeholders to recognize disaster trends and their effects, and enhance prevention, mitigation, and preparedness measures (UNDP & UNDRR, 2022). Current practices show disparities across countries in data recording methods, as well as in governance approaches for managing disaster damage and loss data (ibid.). In the past few decades, there has been a rapid increase in the creation and application of disaster loss databases to inform environmental management and policy decisions (de Sherbinin et al., 2013). Nevertheless, even if a lot has been published regarding the technical aspects of the databases, actual management and uses have received less attention (ibid.).

In general, comparisons of different disaster loss accounting databases show several inconsistencies (Mazhin et al., 2021). Information about disasters and their impacts is fragmented and there is no entity in charge of gathering reliable data (Nakhaei & Bahrampouri, 2016). Moreover, there is no universally agreed standard for assessing and reporting disaster damage (ibid.). The lack of consistent and comparable data is considered a major barrier to effective and long-term loss prevention (Koç & Thieken, 2017).

In March 2015, during the third world conference on disaster risk reduction, the Sendai Framework for Disaster Risk Reduction (SFDRR) was adopted by 187 countries (UNDRR, 2015). It advocates for a significant decrease in disaster risk and losses in lives, people's health, livelihoods and economic, physical, social, and cultural assets of individuals, groups of people, and nations (Migliorini et al., 2019). Moreover, it acknowledges that while the State has the primary responsibility for lowering the risk of disaster, that responsibility should be shared with other stakeholders, such as local governments, the private sector, and other entities (UNDRR, 2015).

The Sendai Framework includes four priorities:

1. Understanding disaster risk in all of its aspects such as vulnerability, capacity, exposure of people and assets, hazard characteristics and the environment.
2. Improving disaster risk governance.
3. Invest in disaster risk reduction.
4. Improve disaster preparedness for efficient response.

Priority for Action 1 specifically targets the use of space-based data and technology. It calls for the promotion of regular updates of location-based risk information to promote real-time access to reliable data and therefore strengthen existing knowledge (ibid.). It is therefore important to provide accurate data on human impacts and disaster-related damage (Mazhin et al., 2021). With more extensive use of disaster loss data, database operators will have a big responsibility to guarantee and maintain the highest possible data quality (Kron et al., 2012). The monitoring and reporting of disaster damage is obligatory for all member nations. Nevertheless, many developing countries have to face a lack of institutional frameworks and the capacity to record disaster loss historical data (Mazhin et al., 2021).

According to Huggel et al., (2015), increased distribution of wealth and exposure of people and assets are key factors influencing changes in disaster losses. While these main drivers have been identified, two main issues received little attention. As identified by Huggel et al., (2015), the first problem is that high-quality databases and connected analyses are not evenly distributed. European countries or the United States are more likely to have studies on disaster events and losses (ibid.). Moreover, countries with a lower GDP are more likely to have less information available at subnational levels due to the poor quality and availability of disaster databases (ibid.). The second issue is that there is not enough research comparing existing disaster databases (Kron et al., 2012). The ways in which data are obtained, reported, and stored have significant impacts on the results of the analysis (ibid.). Consistency in data collection throughout time is particularly important, but this is especially a problem in the developing world where political instability is frequently experienced (Huggel et al., 2015). In order to assess if the economic possibilities of a country have an impact on the state of disaster loss databases, this research will focus on six Latin American countries with different levels of GDP per capita.

The United Nations Office for the Coordination of Humanitarian Affairs (OCHA) examined Latin America and the Caribbean's disaster data between 2000 and 2019 and concluded that it is the second most disaster-prone area worldwide (OCHA, 2020). This is because Latin America is located in the Pacific Ring of Fire, which makes it susceptible to several natural disasters like floods, earthquakes, and volcanic eruptions (Marcillo-Delgado et al., 2021). Between 2015 and 2019 geophysical and climate change-related events had an impact on 35.52 million people and resulted in 4770 fatalities and an estimated cost of 111,545 million dollars (ibid.). OCHA states that most of the data regarding occurrences of natural disasters, people affected, injuries and economic damages are from the EM-DAT database. It is therefore interesting to understand if the data on which the report is based is reliable or not.

Data on disaster damage is extremely important to support policies aimed at reducing disaster risk (Khammar et al., 2019). A common worldwide approach should ideally be used to standardize data collection and recording (ibid.). Global and national database providers must adhere to the same criteria and definitions in order to reduce uncertainty and improve the quality of disaster statistics and information (Wirtz et al., 2012). Important first steps have been made in identifying human casualty indicators and providing geocoding criteria (ibid.). The next steps should be focused on improving data quality and accuracy of disaster loss categories (ibid.).

Today, only a few datasets are publicly available and are therefore widely used: the Emergency Events Database (EM-DAT) which has been maintained by the Centre for Research on the Epidemiology of Disasters (CRED) since 1988, and DesInventar from the United Nations Office for Disaster Risk Reduction (UNDRR) (Koç & Thieken, 2017: EM-DAT, 2016: UNDRR, n.d.). In this thesis, damage estimates recorded in two of the most popular disaster loss accounting databases for six Latin American Countries for the 1900 – 2022 period have been analysed. This thesis' main goal is to compare and contrast the damage estimates for extreme weather events and assess their reliability as well as their current limitations.

Disaster loss databases collect and organize loss data in a central archive (Koç &. Thieken, 2017), and as such the main benefits of developing and using disaster loss databases are:

1. Conduct emergency response, recovery and determine the economic needs.
2. Assess potential risks for future disasters. Past damage data cannot predict future disaster losses with absolute certainty due to climate change and shifting vulnerability patterns. Nevertheless, primary data on past disasters are crucial for validating, readjusting, and creating vulnerability curves in future damage assessments and estimations.
3. Calculate the financial feasibility of investments undertaken to prevent losses.
4. Monitor and evaluate the effect of disasters to meet the worldwide objectives for disaster risk reduction.
5. Conduct thematic analyses (Mazhin et al., 2021).

1.2 Purpose and research questions

Starting from existing practices, I want to examine the state of the art of disaster loss accounting databases and their reliability in measuring disaster impacts and what their current limitations and challenges in recording disaster losses are. Based on the current limitations I will provide some recommendations on how to improve the databases.

My analysis will be guided by two main research questions:

- **Research question 1**: Are disaster loss accounting databases reliable in measuring disaster impacts?
- **Research question 2**: What are the current limitations of existing disaster loss accounting databases?

In this research the word 'reliability' is intended as "the quality of being able to be trusted to do what somebody wants or needs" as well as "the quality of being likely to be correct or true" (Oxford University Press, n.d.).

1.3 Boundaries of the study

This study will analyse disaster loss accounting databases in the context of six Latin American countries, namely, Uruguay, Chile, Costa Rica, Nicaragua, Honduras, and Venezuela. They have been selected following the World Bank's GDP per capita ranking (World Bank, 2021). Uruguay, Chile, and Costa Rica have the highest GDP per capita (excluding the islands) while Nicaragua, Honduras, and Venezuela have the lowest in Latin America (ibid.). The choice to include countries with both the highest and lowest GDP was done to have a more heterogeneous sample and understand if the prosperity of a country has an impact on the state of disaster databases and on its recorded losses.

At present there are four main global disaster databases whose data are used regularly (Moriyama et al., 2018):

1. Sigma, was created by Swiss Re in 1970 and contains data on losses caused by natural hazards and man-made disasters (Swiss Re, 2022).
2. NatCatSERVICE from Munich Re was founded in 1974 and based on an already existing physical repository of loss data. It includes disasters caused by natural hazards and has been constantly adjourned since 1989 (Munich RE, 2011).
3. Emergency Events Database (EM-DAT) from the Centre for Research on the Epidemiology of Disasters (CRED) at Leuven University in Belgium was established in 1988 with initial support from the World Health Organization (WHO) and the Belgian Government (CRED, n.d.). It is publicly accessible and therefore the most frequently quoted database (Kron et al., 2012).
4. DesInventar from the United Nations Office for Disaster Risk Reduction (UNDRR) and the United Nations Development Programme (UNDP) was established in 1994. It is publicly available, and includes all disasters with one or more human losses (UNDRR, n.d.).

Due to accessibility issues, this research will only focus on data collected from EM-DAT and DesInventar. Being interested in the reliability of these databases in measuring the impacts of disaster events, I will only focus on natural hazards common between the databases. In particular, I will consider droughts, floods, earthquakes, landslides, and storms. Regarding the indicators I will mainly focus on human-centred indicators with comparable definitions such as number of deaths, people affected, and people injured.

2. Conceptual Framework

The United Nations Framework Convention on Climate Change (UNFCCC, 2012) defines loss and damage as the actual or potential negative impacts on human and natural systems due to climate change manifestations. Loss is defined as those negative impacts for which there is no possible reparation or restoration and damage as those negative impacts for which reparation or restoration is possible (ibid.). The distinction between reversible and irreversible losses is a new concept for the disaster risk management community which uses words such as 'loss', 'damage', 'cost', and 'impact' interchangeably despite their specific definitions (Gall, 2015). Another distinction can be made between direct and indirect losses. When a loss results from a direct physical injury from the hazard such as a structure collapsing, crops being destroyed, or someone drowning, is referred to as a direct loss (UNDRR, n.d.). An indirect loss is any subsequent consequence brought on by physical destruction (ibid.).

In the past, the disaster risk community and the insurance industry were the only two sectors interested in assessing the effects of disasters (Gall, 2015). In this sense, losses and damages were only considered as an assessment of the harm caused by a disaster event (ibid.). Nevertheless, the relationship between the magnitude of an event and resilience is defined as "the ability of a system, community, or society exposed to hazards to resist, absorb, accommodate to, and recover from the effects" (UNDRR, n.d.). Their connection becomes evident in the different loss patterns between high and low GDP countries (Gall, 2015). Quantifying losses requires more than just evaluating the damage caused by a disaster; it also involves assessing the performance of risk management techniques (ibid.). In this sense, disaster loss databases could help in answering some questions such as how and where to decrease losses, and how much investment is required. Increasing loss for the same event size might be regarded as maladaptation to the climate or poor disaster risk management; on the other hand, decreased loss in extremely sensitive areas is evidence of successful applications of risk management techniques or climate adaptation (ibid.).

Different approaches can be employed to promote global strategies for disaster risk reduction and management, depending on the priorities and actors involved (Migliorini et al., 2019). These actions may include establishing the impacts of disasters, disseminating effective risk reduction tools, outlining socio-economic processes to encourage the involvement of new resources, and promoting preparedness (ibid.). According to De Groeve et al., (2013), there are three main conceptual models for the use of disaster loss data. Loss data can be used for accounting, forensic analysis of disasters, and risk modelling (ibid.). Since I have already discussed what loss accounting is, I will focus on the other two models. Disaster forensics involves examining the progression of a disaster and identifying its causes (Masys, 2016). By drawing insights from this analysis, professionals and policy makers can direct the reconstruction processes, and more importantly, evaluate potential hazards and apply strategies to reduce risk in comparable areas with similar aspects and vulnerabilities (ibid.). Risk modelling entails a more comprehensive approach. Its objective is to enhance risk evaluations and prediction techniques by using loss data to understand vulnerabilities and to determine the specific sectors needing risk reduction and mitigation measures (De Groeve et al., 2013). To accurately align documented losses with the outcomes of comprehensive hazard models, additional information is required regarding the spatial, temporal, and quantitative uncertainties (ibid.). Figure 1 summarizes the key aspects of loss accounting, disaster forensics, and risk modelling. The use of such a system would establish clear objectives and scopes for the collected data that can be then used at different levels, from local to global (ibid.).

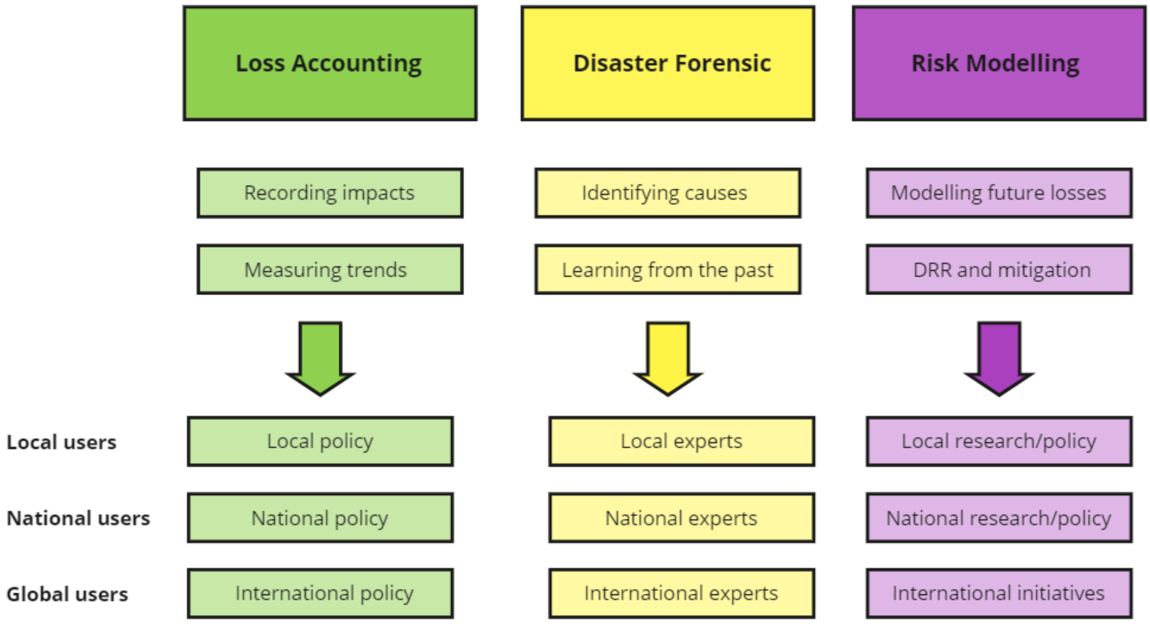

Figure 1. Key aspects of loss accounting, disaster forensics, and risk modelling. Framework taken from (De Groeve et al., 2013).

3. Method and material

Disaster data analyzed in this study are taken from two of the most used global disaster loss accounting databases, EM-DAT and DesInventar. As described in the boundaries of the study section, there are more databases available, but they will not be considered due to accessibility issues. The countries selected for this analysis are: Uruguay, Chile, Costa Rica, Nicaragua, Honduras, and Venezuela.

My analysis has been based on primary quantitative data directly downloaded from the databases' websites. For EM-DAT I downloaded all disasters classified as "natural" that occurred in a time span ranging from 1900 to 2022 in the America region. I was not able to choose the specific countries I was interested in, but they were manually selected later on. DesInventar, allows you to select specific countries, but it does not give the option to filter for disaster type or time span. Since there is a very limited number of entries prior to 1900, those have been excluded from the analysis. Once all the data was downloaded, relevant information was manually identified and selected.

Before describing how data was prepared and analyzed it is relevant to provide a description of the two main sources used in this analysis.

3.1 EM-DAT description

The Emergency Event Database (EM-DAT) was developed in 1988 by the Centre for Research on the Epidemiology of Disasters (CRED) with support from The World Health Organization (WHO) and the Université Catholique de Louvain, Belgium. (CRED, n.d.). The database's primary goal is to support humanitarian efforts on a national and worldwide scale. This initiative wants to offer an objective foundation for vulnerability assessment and priority setting, as well as to rationalize decision-making for disaster preparedness (ibid.).

EM-DAT's data come from United Nations agencies, non-governmental organizations, insurance companies, academic institutions, and the media (Huggel et al., 2015). The database only provides a generic description of their data sources, and it is not possible to trace the origin of each entry.

The two main disaster categories present in the database are natural and technological (CRED, n.d.). Natural events are then divided into a number of subgroups including geophysical, meteorological, hydrological, climatological, and biological disasters (ibid.). Each of those subgroups is again classified into more specific disaster types such as floods, landslides, avalanches, etc. Each entry has a unique identifier, and they provide information about the exact location inside the country, the origin of the event, and the presence of secondary disaster events. The loss indicators they use are total deaths, number of injured, number of affected, total affected, number of homeless and total damages in US dollars.

To report a disaster in EM-DAT at least one of the following requirements must be met (CRED, 2009):

- Ten or more fatalities have been recorded,
- One hundred or more people have been impacted by the disaster,
- The declaration of the emergency state,
- A request for internal assistance has been made.

3.2 DesInventar description

The DesInventar approach was developed in 1994 by the Network for Social Studies on Disaster Prevention in Latin America (LA Red) to collect disaster data in Latin America (UNDRR, n.d.). The United Nations Office for Disaster Risk Reduction (UNDRR) and the United Nations Development Programme (UNDP) later started supporting this idea and implemented similar systems in the Caribbean, Asia, and Africa (ibid.).

DesInventar was developed to systematically collect information about the frequency of small and medium and large scale disasters starting from pre-existing official data (ibid.). Today, approximately 23 national-level databases on technological and natural disasters are kept up to date by the DesInventar open-source disaster information management system (ibid.).

DesInventar focuses mainly on news media as a priority source even though it also uses data from government agencies, NGOs, and academic institutions (Huggel et al., 2015). Differently from EM-DAT, each disaster entry is linked to its source.

In order to assess risks in particular locations, the DesInventar methodology suggests using historical data regarding the effects of disasters. These data have been systematically and uniformly gathered following a set of criteria which are, to be time-stamped, geo-referenced and connected to a small geographic area (UNDRR, n.d.). It is the responsibility of each country to store the data in a uniform format and to maintain and update the database (Moriyama et al., 2018).

There are no main disaster categories or subgroups. Each disaster is defined by the 'event name' and each country includes different types of events. The database includes extreme weather events, seismic hazards, but also generic accidents, explosions, and car crashes. The same goes for the loss accounting indicators. It includes more common and generic ones such as number of deaths, number of affected, and economic losses, but also extremely specific ones such as forest loss, loss of cattle, and destroyed health facilities.

The DesInventar database includes all kinds of events with one or more human losses, or one or more dollars of economic losses (ibid.). Table 1 summarizes the key characteristics of both databases.

Table 1 EM-DAT and DesInventar summary table.

	EM-DAT	DesInventar
Spatial resolution	Country	Country
Temporal coverage	1900- present	It depends on the country.
Entry thresholds	- Ten or more fatalities have been recorded, - One hundred or more people have been impacted by the disaster, - The declaration of the emergency state, - Request for internal assistance.	- One or more human losses - One or more dollars in economic losses
Data sources	United Nations agencies, non-governmental organizations, insurance companies, academic institutions, and media	Press, government agencies, NGOs, and academic institutions
Owner	Centre for Research on the Epidemiology of Disasters, Université Catholique de Louvain, Belgium.	It depends on the country

3.3 Data preparation & analysis

In order to study the main differences between EM-DAT and DesInventar, I focused on analysing quantitative reporting differences for the same indicators and disaster events.

Once all the data have been downloaded in an Excel format, I hand-matched disaster events common across the two databases. The entries where the match was not straightforward e.g., due to missing data were left behind. The matching was done following a set of criteria:

1. Check if disaster events have the same Global Identifier number (GLIDE). It is a globally used unique ID code that allows to easily identify disasters (ADRC, 2004). If two entries on different databases have the same GLIDE number, then it is assumed that that they are the same event (ibid).
2. If the GLIDE number is not present, hand-match the remaining events by considering the disaster type, date of occurrence, and geographic location (Panwar & Sen, 2019).

While EM-DAT reports the cumulative damage of an event specifying the start and end date, DesInventar reports the damages separately, registering a new entry for each day. This means that, if for example there was a flood in Costa Rica from 10/02/2010 until 15/02/2010, EM-DAT would create one single entry reporting a sum of all the damages, while DesInventar would add six different flood events. To facilitate the comparison, I summed all the entries for the same event in DesInventar so that they are in a format similar to that of EM-DAT.

Disaster events and indicators that were not common across both databases have been left out because they were not interesting for the scope of the analysis. The selected disaster types are drought, earthquake, extreme temperature, flood, landslide, storm, volcanic activity, and wildfire. EM-DAT and DesInventar do not have a shared disaster terminology. As a result, the same events are often reported with slightly different names. For example, 'extreme weather events' in EM-DAT corresponds to 'heat wave' or 'ola de frìo' (cold wave) in DesInventar, and 'wildfire' on EM-DAT is equal to 'forest fire' on DesInventar. The choice of selected disaster types was made by comparing the disaster type definitions on the glossary pages of both databases. Events with different disaster types were matched only if the event definitions were similar. Moreover, DesInventar does not only use English to name its indicators, and often changes to the local language. Every time this happened, I translated the name of the event in English and checked the corresponding definition on the database's glossary page. Table 2 shows the definitions of the selected disaster events.

Table 2 Disaster events definitions form EM-DAT and DesInventar. CRED (n.d.), UNISDR (2019)

Event	**EM-DAT**	**DesInventar**
Drought	An extended period of unusually low precipitation that produces a shortage of water for people, animals and plants. Drought is different from most other hazards in that it develops slowly, sometimes even over years, and its onset is generally difficult to detect. Drought is not solely a physical phenomenon because its impacts can be exacerbated by human activities and water supply demands. Drought is therefore often defined both conceptually and operationally. Operational definitions of drought, meaning the degree of precipitation reduction that constitutes a drought, vary by locality, climate and environmental sector (CRED, n.d.).	Unusually dry season, without rain or with rain deficit. As a whole, these are long periods (months, years, and even decades) typical in limited continental areas or on regional scales (UNISDR, 2019, page 53).
Earthquake	Sudden movement of a block of the Earth's crust along a geological fault and associated ground shaking (CRED, n.d.).	All movements in the earth's crust causing any type of damage or negative effect on communities or properties. The event includes terms such as earth tremor, earthquake and vibration (UNISDR, 2019, page 53).
Extreme temperature	Heat wave: A period of abnormally hot and/or unusually humid weather. Typically, a heat wave lasts two or more days. The exact temperature criteria for what constitutes a heat wave vary by location (CRED, n.d.).	Heat wave: Rise of atmospheric average temperature well above the averages of a region, with effects on human populations, crops, properties and services (UNISDR, 2019, page 54).
	Extreme winter conditions: Damage caused by snow and ice. Winter damage refers to damage to buildings, infrastructure, traffic (esp. navigation)	Cold wave: Drop of atmospheric average temperature well below the averages of a region, with effects on

	inflicted by snow and ice in form of snow pressure, freezing rain, frozen waterways etc. (CRED, n.d.).	human populations, crops, properties and services (UNISDR, 2019, page 53).
Flood	A general term for the overflow of water from a stream channel onto normally dry land in the floodplain (riverine flooding), higher-than- normal levels along the coast and in lakes or reservoirs (coastal flooding) as well as ponding of water at or near the point where the rain fell (flash floods) (CRED, n.d.).	Water that overflows river-bed levels and runs slowly or quickly on small areas or vast regions (UNISDR, 2019, page 54).
Landslide	Any kind of moderate to rapid soil movement incl. lahar, mudslide, debris flow. A landslide is the movement of soil or rock controlled by gravity and the speed of the movement usually ranges between slow and rapid, but not very slow. It can be superficial or deep, but the materials have to make up a mass that is a portion of the slope or the slope itself. The movement has to be downward and outward with a free face (CRED, n.d.).	All mass movements other than surface erosion of a hillside. This event includes terms such as precipitation of earth, settling, horizontal land thrust, mass movement, displacement, subsidence, collapse of caves or mines, rock falls, (slow or quick) detachment of soil masses or rocks on watersheds or hillsides (UNISDR, 2019, page 54).
Storm	A type of meteorological hazard generated by the heating of air and the availability of moist and unstable air masses. Storms range from localised thunderstorms (with heavy rain and/or hail, lightning, high winds, tornadoes) to meso-scale, multi-day events (CRED, n.d.).	Rain accompanied by strong winds and/or electric discharges (lightning) (UNISDR, 2019, page 55).
Volcanic activity	A type of volcanic event near an opening/vent in the Earth's surface including volcanic eruptions of lava, ash, hot vapour, gas, and pyroclastic material (CRED, n.d.).	Volcanic eruption with disastrous effects: eruption and emission of gas and ashes, stone falls (pyroclast), flows of lava, etc. (UNISDR, 2019, page 54).
Wildfire	Any uncontrolled and non-prescribed combustion or burning of plants in a natural setting such as a forest, grassland, brush land or tundra, which consumes the natural fuels and spreads based on environmental conditions (e.g., wind, topography). Wildfires can be triggered by lightning or human actions (CRED, n.d.).	The event includes all open-air fires in rural areas, natural and artificial forests, plains, etc. (UNISDR, 2019, page 56).

After the hand matching was completed, I wanted to study the degree of similarity between the different databases. Specifically, I wanted to understand if for the same disaster event and indicator the selected databases report the same numerical data or, if they vary and if so by how much they differ. The Sendai Framework's indicators and definitions have been used as a guide. Common indicators across the databases were number of deaths, number of injured, and number of affected. Similar to the disaster types, the loss indicators had slightly different names as well. Only indicators with similar definitions were selected and compared. Table 3 shows the different definitions for the selected indicators. In most of the cases, finding analogous indicators in the two databases was a straightforward process. The only case that required further explanation was the case regarding the number of people affected. While EM-DAT uses the indicators ‘affected’ as “people needing immediate assistance to cover their basic needs during an emergency” and ‘total affected’ as “the sum of injured, affected, and homeless” (CRED, n.d.), DesInventar differentiates between ‘directly affected’ and ‘indirectly affected’. The first refers to immediate direct damages to livelihoods, health, and economy, while the second one is more connected to the long-term consequences of a disaster (UNISDR, 2019). For the analysis, I compared ‘total affected’ from EM-DAT and ‘directly affected’ from DesInventar because they both cover the immediate consequences people face after a disaster including people who are injured or who are left homeless.

Table 3 Key indicators and definitions. CRED (n.d.), UNISDR (2019), UNISDR (2015).

Indicator	**EM-DAT**	**DesInventar**	**Sendai Framework**
Deaths	Number of people who lost their life because the event happened (CRED, n.d.).	The number of persons whose deaths were directly caused (UNISDR, 2019).	The number of people who died during the disaster, or directly after, as a direct result of the hazardous event (UNISDR, 2015, page 7).
Injured	People suffering from physical injuries, trauma or an illness requiring immediate medical assistance as a direct result of a disaster (CRED, n.d.).	The number of persons whose health or physical integrity is affected as a direct result of the disaster. This figure does not include victims who die. Those who suffer injuries and or illness, if the event is related to a plague or epidemic, should be included here (UNISDR, 2019).	The number of people whose whereabouts is unknown since the hazardous event. It includes people who are presumed dead, for whom there is no physical evidence such as a body, and for which an official/legal report has been filed with competent authorities (UNISDR, 2015, page 7).
Affected	People requiring immediate assistance during a period of emergency, i.e. requiring basic survival needs such as food, water, shelter, sanitation and immediate medical assistance (CRED, n.d.).		
Total affected	The sum of the injured, affected and left homeless after a disaster (CRED, n.d.).		People who are affected, either directly or indirectly, by a hazardous event. Directly affected are those who have suffered injury, illness or other health effects; who were evacuated, displaced, relocated or have suffered direct damage to their livelihoods,

			economic, physical, social, cultural and environmental assets (UNISDR, 2015, page 19).
Directly affected		People who have suffered injury, illness or other health effects; who were evacuated, displaced, relocated; or have suffered direct damage to their livelihoods, economic, physical, social, cultural and environmental assets (UNISDR, 2019).	People who have suffered injury, illness or other health effects; who were evacuated, displaced, relocated; or have suffered direct damage to their livelihoods, economic, physical, social, cultural and environmental assets (UNISDR, 2015, page 19).
Indirectly affected		People who have suffered consequences, other than or in addition to direct effects, over time due to disruption or changes in economy, critical infrastructures, basic services, commerce, work or social, health and physiological consequences (UNISDR, 2019).	People who have suffered consequences, other than or in addition to direct effects, over time due to disruption or changes in economy, critical infrastructures, basic services, commerce, work or social, health and physiological consequences (UNISDR, 2015, page 19).

Once all data was matched, the events were examined by using graphic representations and percentages of commonalities and discrepancies. I compared the temporal frame for all the recorded events in Uruguay, Chile, Costa Rica, Honduras, Venezuela, and Nicaragua. Then, only the differences between indicators and countries have been studied for matched events. I preferred to only focus on common events because this study aims to understand if loss accounting databases are reliable in measuring the impact of disaster events. Comparing all the events present in the databases would not give any insights to answer my research questions. Figure 2 summarizes the key analytical steps.

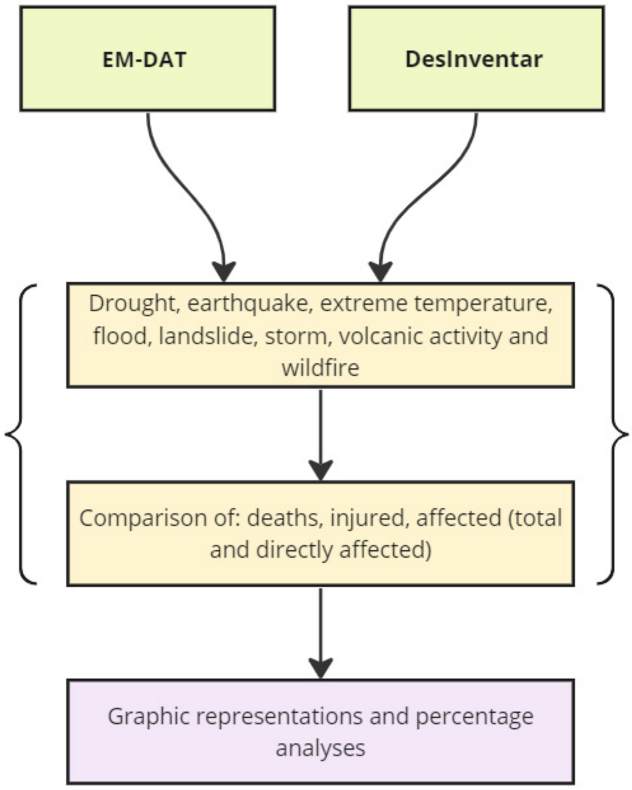

Figure 2. Analytical steps. Inspired from Panwar & Sen (2019).

As a second analysis, I selected two events from all the matched cases, and I compared the information contained in the databases with what was reported by media articles and journals. This was an effort to triangulate and get additional information on these disaster events from other sources. The two selected events were those with the biggest media resonance and the biggest discrepancies across the databases. I also tried to contact the databases' owners to seek clarification on the databases and sources, but it was not possible to organize a meeting within the timeframe of the thesis.

4 Results

Results are structured following five main sections. The first one gives an overview of the volume of data analysed and of the percentages of matching events. The second section describes the temporal coverage of the databases and the remaining sections cover the analysis of the three selected indicators; number of deaths, injured and affected.

4.1 Volume analysed and percentage analysis

The results section begins with an overview of the volume of data analysed in this study. As explained in the methodology, the event types considered in the research are drought, earthquake, extreme temperature, flood, landslide, storm, volcanic activity, and wildfire for Uruguay, Chile, Costa Rica, Honduras, Venezuela, and Nicaragua within a time frame from 1900 to 2022. Table 4 shows the total count of records analysed in this study for both EM-DAT and DesInventar. The number of records in DesInventar is much higher compared to EM-DAT. EM DAT has 11973 fewer entries than DesInventar for the same time frame and disaster indicators. This can be due to its restrictive entry criteria summarized in Table 1.

Table 4 Total counts of records

Source	Count of Records
EM-DAT	4107
DesInventar	16080

Table 5 shows the total count of records per country for EM-DAT and DesInventar.

Table 5 Count of records per country

Source	Count of records per country					
	Uruguay	Chile	Costa Rica	Honduras	Nicaragua	Venezuela
EM-DAT	31	86	64	82	67	62
DesInventar	1283	2388	5520	2801	681	3407

Table 6 is showing the number of matched events per country and in total. By comparing these numbers with the count of records per country (Table 5) it is possible to see that not all the events in EM-DAT have been matched with those in DesInventar. It is assumed that all EM-DAT events should be in the DesInventar database, but it was not possible to match them due to missing data.

Table 6 Number of matched events

Country	Total number of matched events
Uruguay	12
Chile	42
Costa Rica	37
Honduras	29
Venezuela	20
Total	140

Starting from the total counts of records, all the events in EM-DAT with the ones in DesInventar were compared. Table 7 shows the total percentage of matching events between the two databases as well as the matching percentages for each country. 5.1% of the data contained in Table 4 are common events between EM-DAT and DesInventar. The remaining 94.9% were not possible to match or were recorded only on one of the two databases. Percentages of matching events per country are low. Chile has the lowest matching rate with 2.4% and Nicaragua has the highest one with 12.8%. Percentages were expected to be low due to the large differences in the number of events contained in the two databases.

Table 7 Percentage of matching events

Country	Percentage of matching events
Uruguay	8.2%
Chile	2.4%
Costa Rica	6.1%
Honduras	5.7%
Venezuela	4.9%
Nicaragua	12.8%
Total	**5.1%**

Table 8 shows the total percentage of missing data per country for the indicators 'number of deaths', 'injured', and 'affected', while only considering common events. In the DesInventar database, for all countries assessed more than half of the data for the selected indicators was missing, with Honduras having the highest percentage of missing data at 83%. On average EM-DAT has lower percentages of missing data when compared to DesInventar, but they are still significantly high.

Several researchers state that the GDP of a country can have an impact on the quality of the databases and on the number of missing data (Wirtz et al., 2012; Huggel et al., 2015; Khammar et al., 2019; Brock & Rathburn, 2022). Table 8 shows the percentage of missing data per country with Uruguay having the highest GDP and Nicaragua having the lowest (World Bank, 2021). Overall, there are no big differences between high and low GDP countries. Interestingly, Uruguay is the country with the highest GDP and the highest percentage of missing data (56%), while Nicaragua, with the lowest GDP, has the lowest missing data percentage (30%) according to EM-DAT.

Table 8 Percentage of missing data per country for matching events

Country	Percentage of missing data EM-DAT	Percentage of missing data DesInventar
Uruguay	56%	69%
Chile	34%	47%
Costa Rica	33%	58%
Honduras	36%	83%
Nicaragua	30%	54%
Venezuela	40%	56%

4.1 Temporal coverage

The second step of the analysis was the comparison of the temporal coverage between EM-DAT and DesInventar. I first compared the difference in the number of events per year for both databases. In order to assess the temporal coverage, the total number of events and not the hand matched ones were considered. Figure 3 and Figure 4 show the number of events per year for EM-DAT and DesInventar.

Both EM-DAT and DesInventar have records of events from 1900, but they become more consistent from 1971. While EM-DAT keeps recording events until 2022 the last event recorded in DesInventar is from 2019. The lack of updates of the DesInventar depend on the organization responsible to manage the database. As shown in Figure 5 there is a significant difference in the number of events per year between the two databases with DesInventar having much higher numbers.

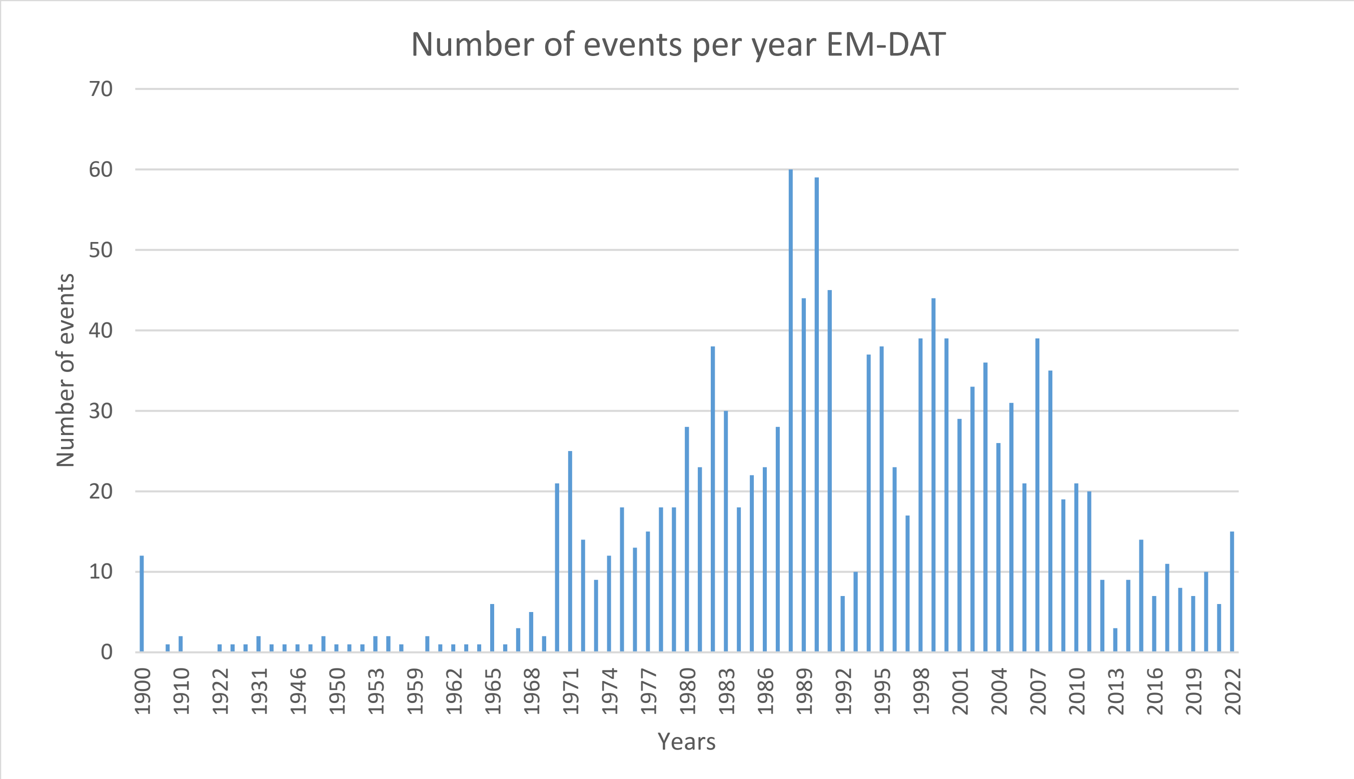

Figure 3 Number of events per year EM-DAT

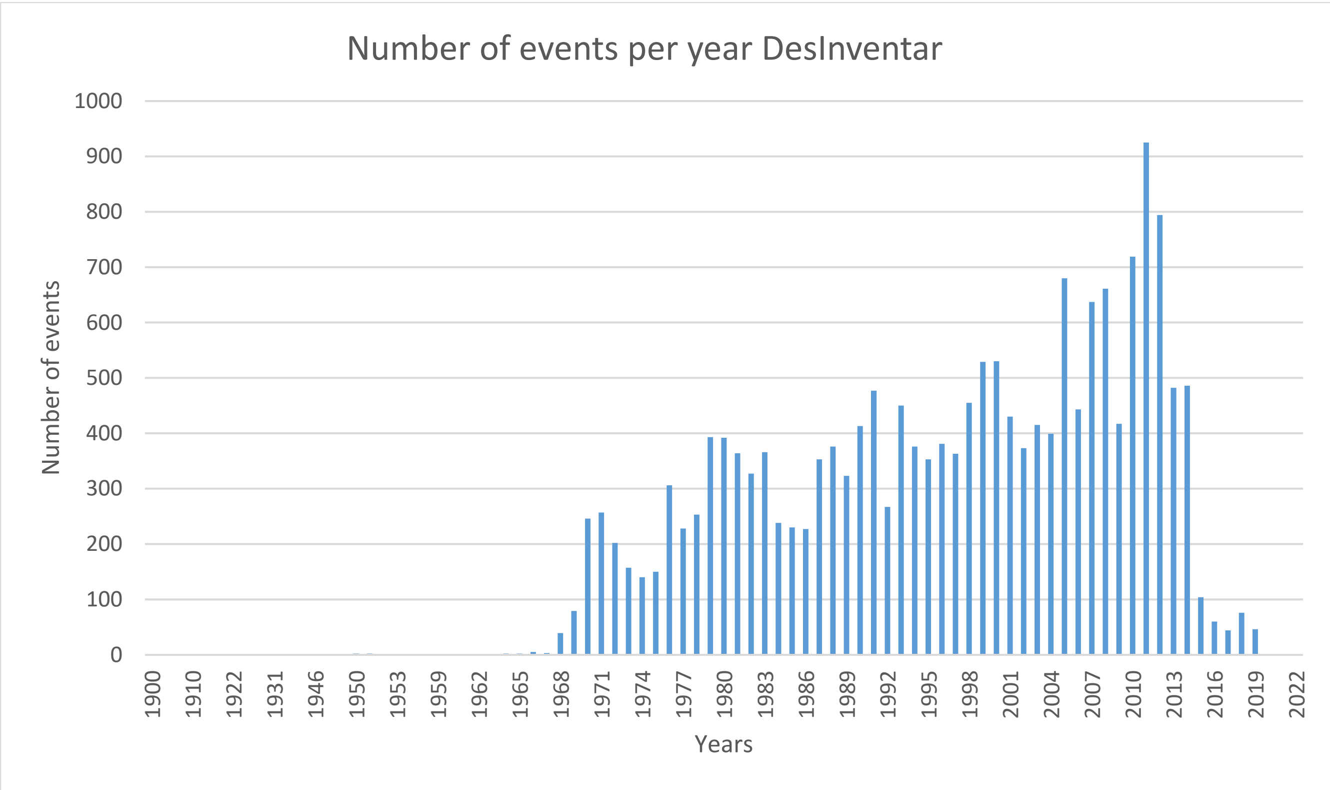

Figure 4 Number of events per year DesInventar

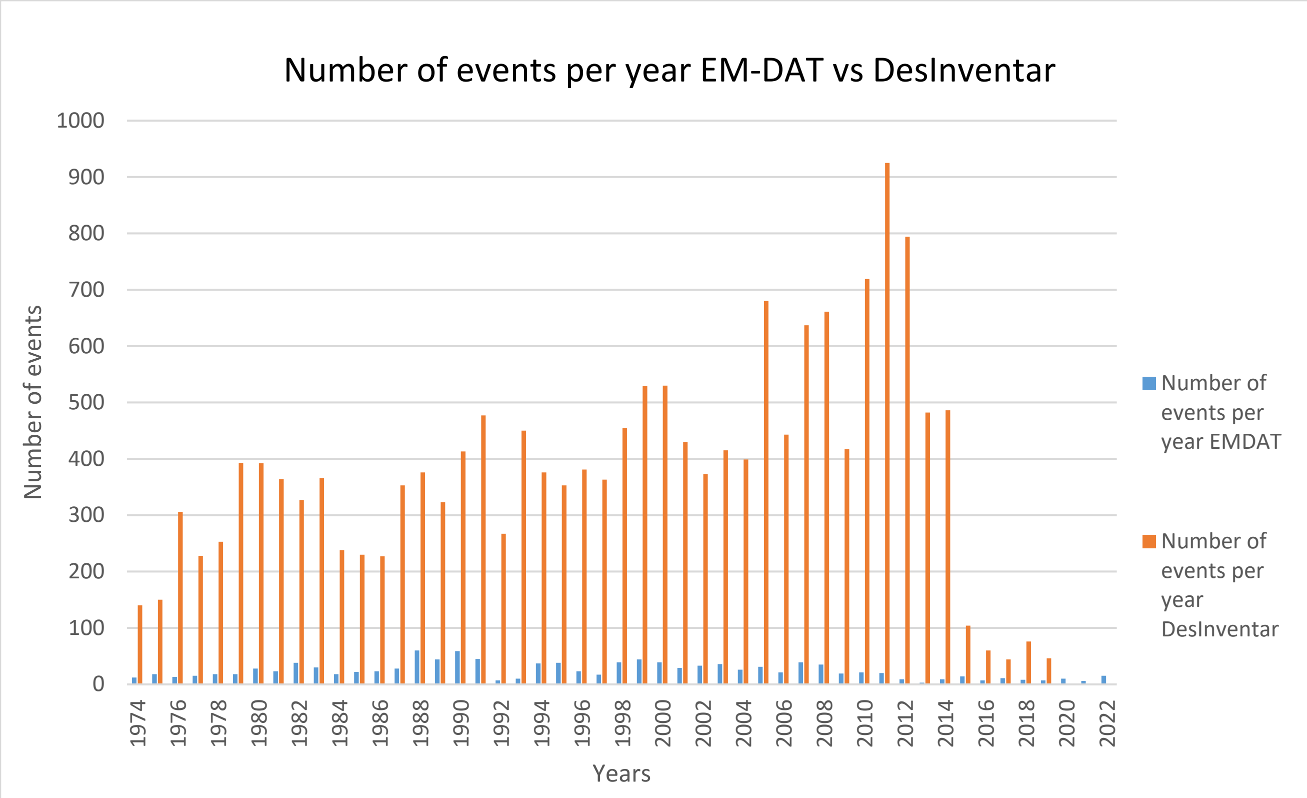

Figure 5 Number of events per year EMDAT vs. DesInventar.

Figure 6 shows the number of events per country in EM-DAT and DesInventar. As for the temporal coverage, I considered the total number of events and not only the matched ones. Chile has the highest number of events per year according to both databases, while Nicaragua has the lowest number of events per year. The graph shows the high variability between the datasets, with DesInventar constantly reporting a higher number of events. There is no pattern in the ratio between the datasets that could be used to predict the difference between the databases.

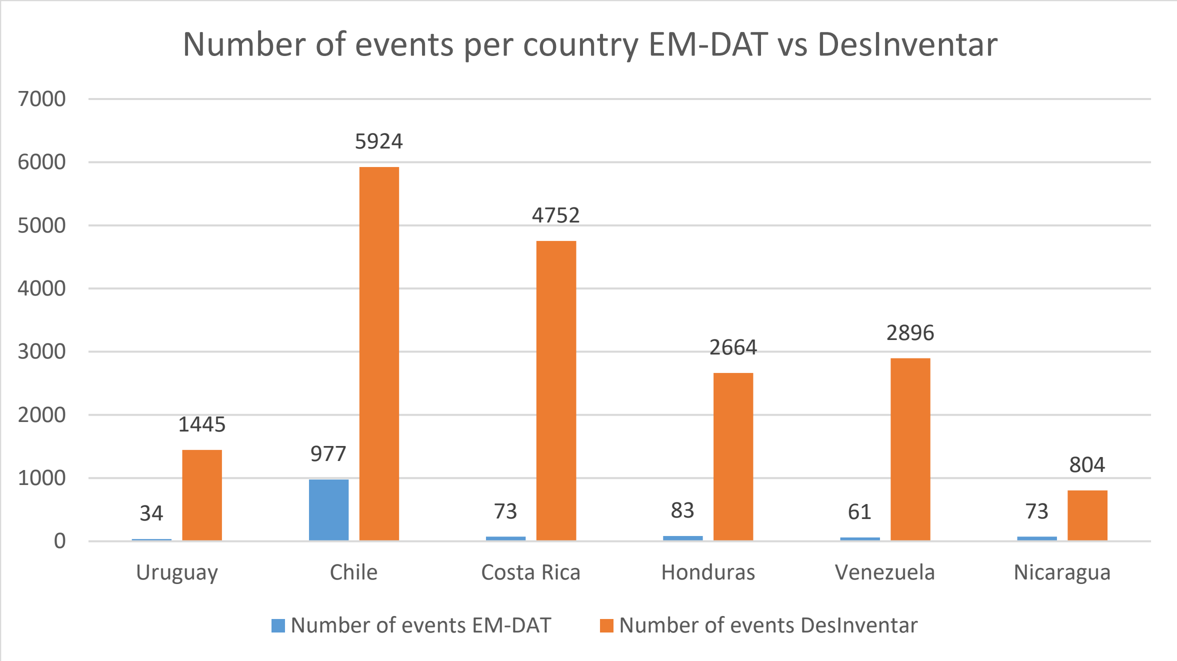

Figure 6 Number of events per country EM-DAT vs DesInventar.

Figure 7 shows the total number of matched events per year in each country. The first events on both EM-DAT and DesInventar date back to 1900, but the first matched event was only in 1950 while the last one occurred in 2018. On average there are two matched events per year per country with 2005 and 2010 as the years with the highest total number of matched events. This could be due to the higher number of events registered on the two databases for both years.

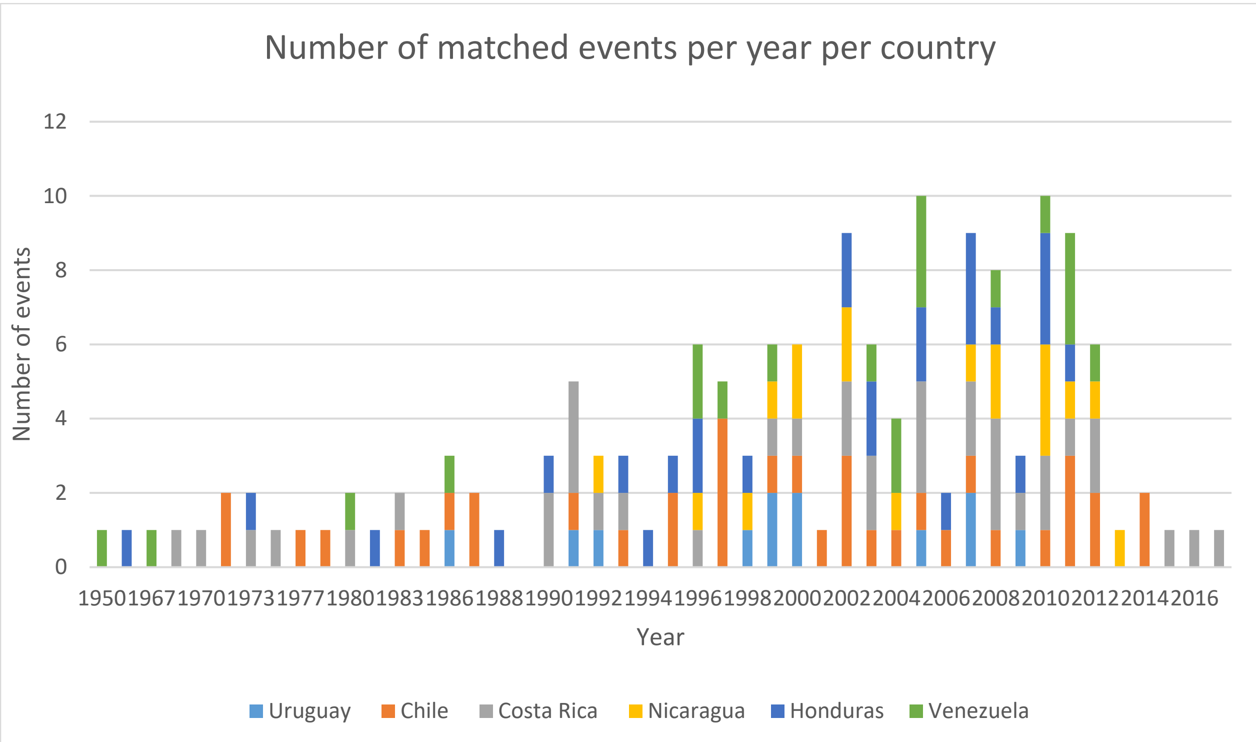

Figure 7 Number of events per year per country

4.2 Number of deaths

Figure 8 and Figure 9 show the number of deaths per year for EM-DAT and DesInventar for the matched events. Ideally, they should show the same number of deaths per year and should follow a similar trend, but they do not. EM-DAT consistently reports a higher number of deaths with a peak in 1999. The biggest outlier is year 2000. While EM-DAT reports 30012 deaths, DesInventar reports 66. Only in 2010, were the recorded number of deaths is similar for both databases, with 723 deaths reported in EM-DAT and 668 deaths in DesInventar.

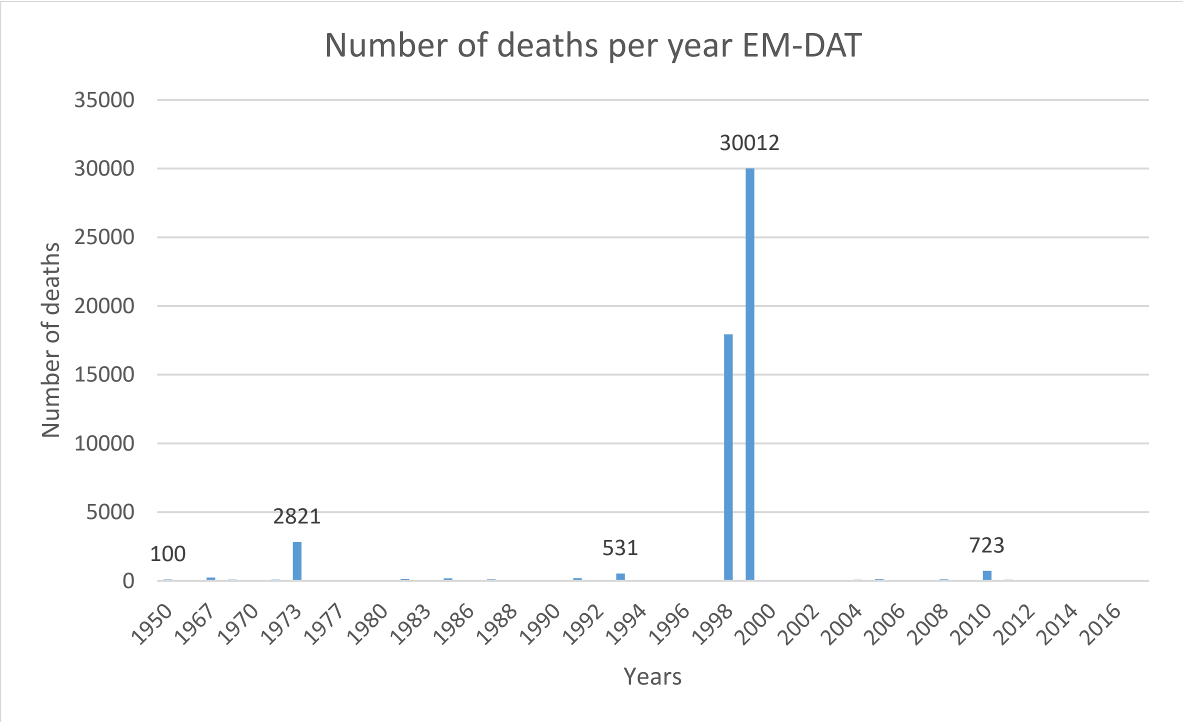

Figure 8 Number of deaths per year EM-DAT (matched events)

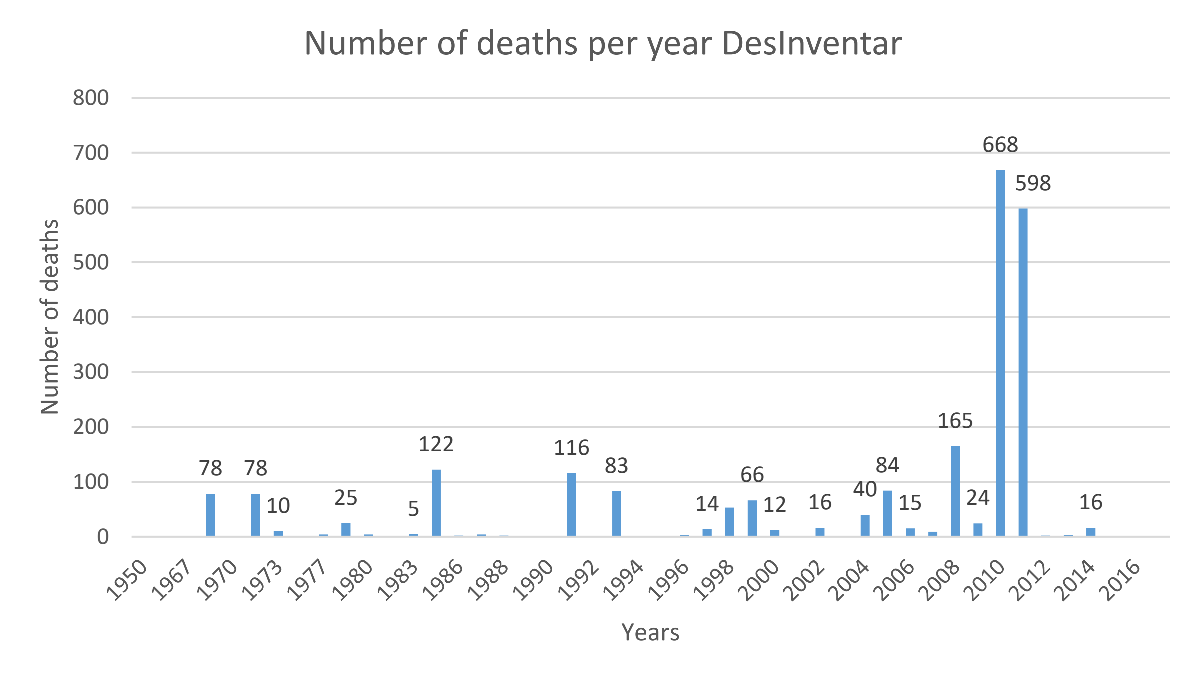

Figure 9 Number of deaths per year DesInventar (matched events)

Figure 10 shows the number of deaths per country. Again EM-DAT reports a much higher number of deaths than DesInventar. The biggest difference is for Venezuela with EM-DAT reporting 30 424 more deaths than DesInventar.

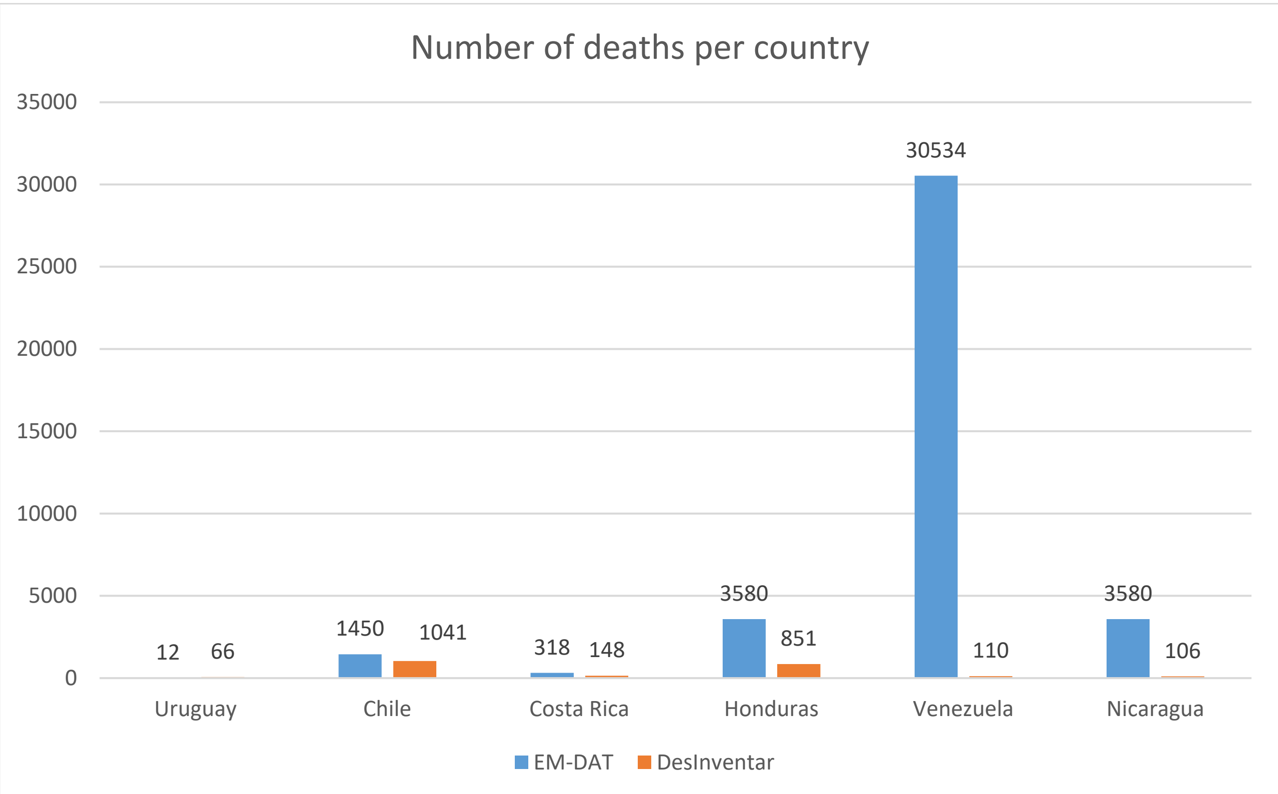

Figure 10 Number of deaths per country (matched events)

The big disproportion between the number of deaths reported in the two databases could be due to the high occurrence of missing data. For the indicator 'deaths', 27% of the data is missing in EM-DAT and 59% in DesInventar. This means that in DesInventar, more than half of the data for this indicator has not been recorded. These percentages have been calculated only considering common events.

4.3 Injured

Figure 11 and Figure 12 show the number of injured people per year on EM-DAT and DesInventar. As for the number of deaths, only the matched events were considered. Therefore, the numbers reported between the datasets should be the same or very close to each other. Nevertheless, EM-DAT is consistently reporting a higher number of injured, in some cases there was an extreme difference between the datasets. For example, in 1998 EM-DAT reported 12228 injured while DesInventar only reported 31. 2014 seems to be the only year with the exact same number of injured reported in both databases.

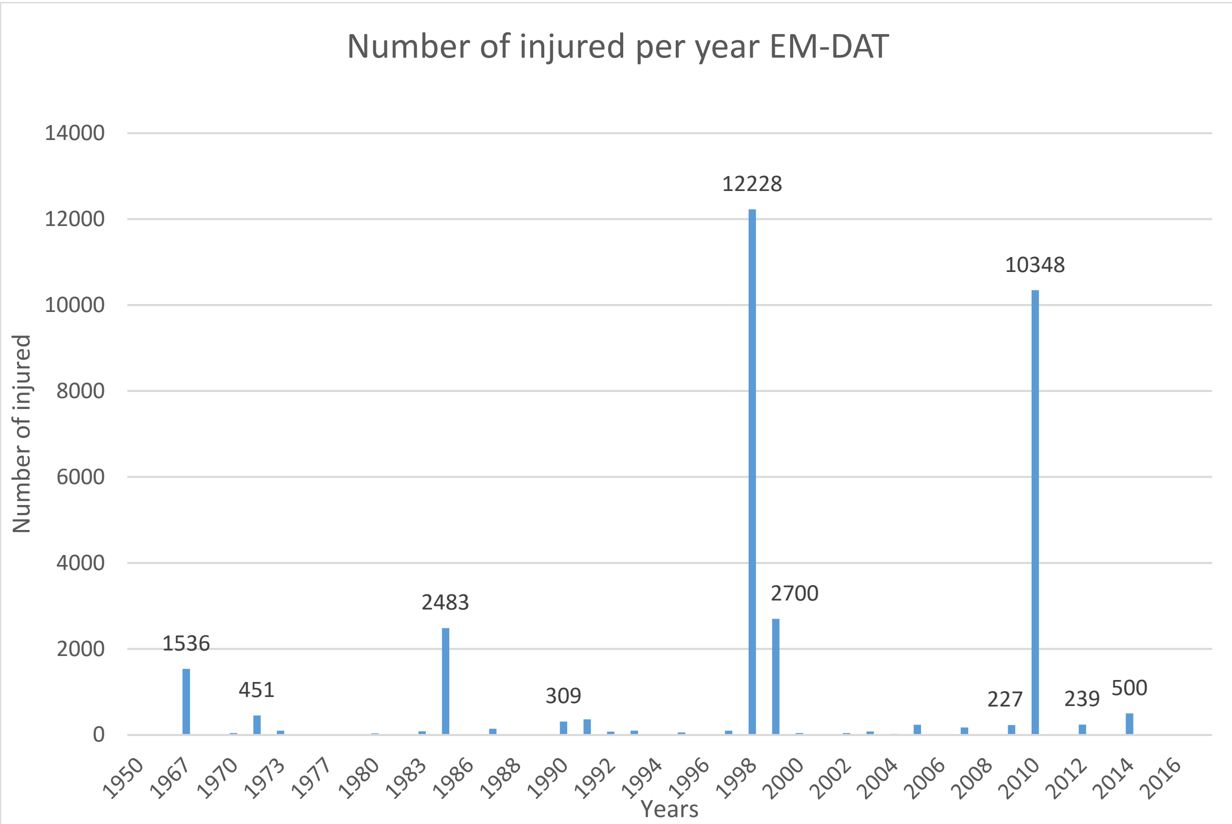

Figure 11 Number of injured per year EM-DAT (matched events)

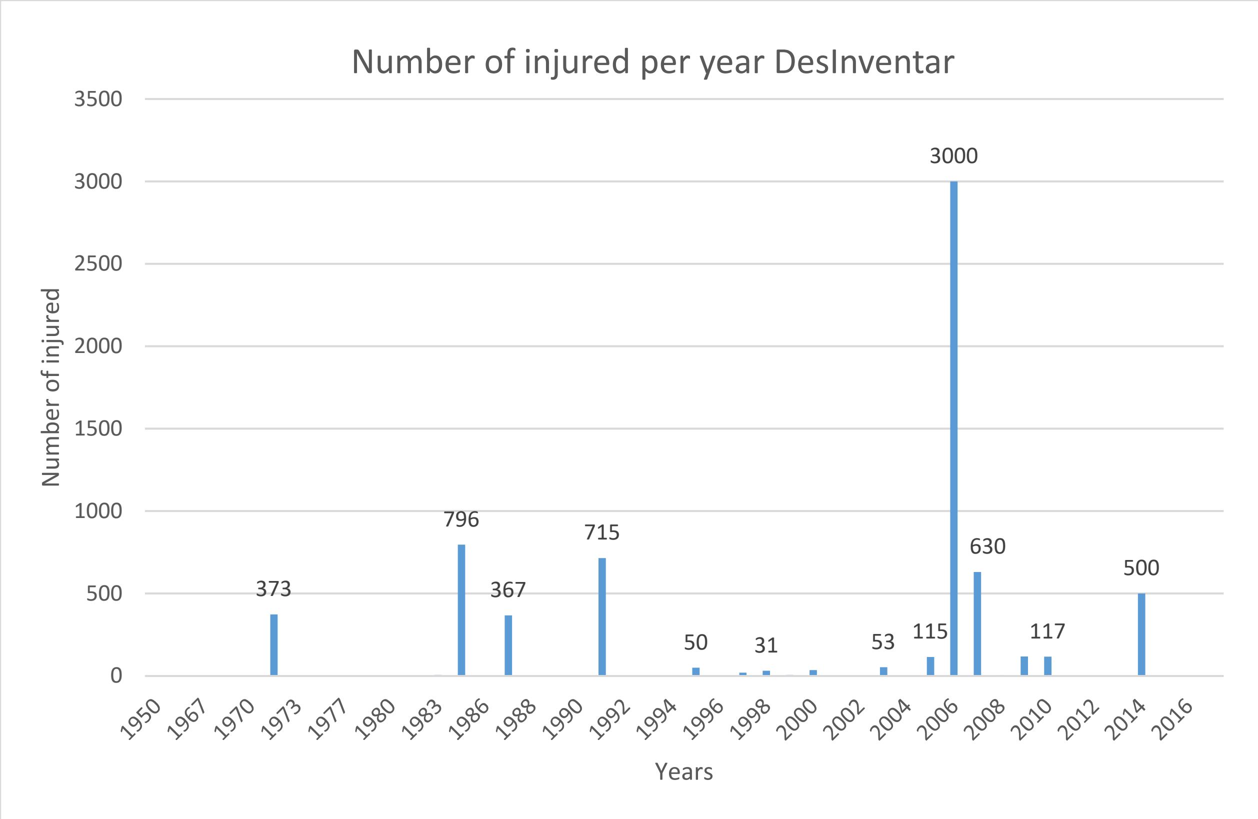

Figure 12 Number of injured per year DesInventar (matched events)

Figure 13 shows the number of injured people per country. It confirms that EM-DAT consistently reports higher numbers, with an extreme case in Venezuela where there are zero injured recorded in DesInventar and 4319 in EM-DAT. Since I am only considering the events that are common across the two databases the low number of injured recorded in DesInventar is probably not because there have not been injured people during the disasters but due to a high amount of missing data. It is also true that these differences could also be caused by EM-DAT that is constantly overreporting.

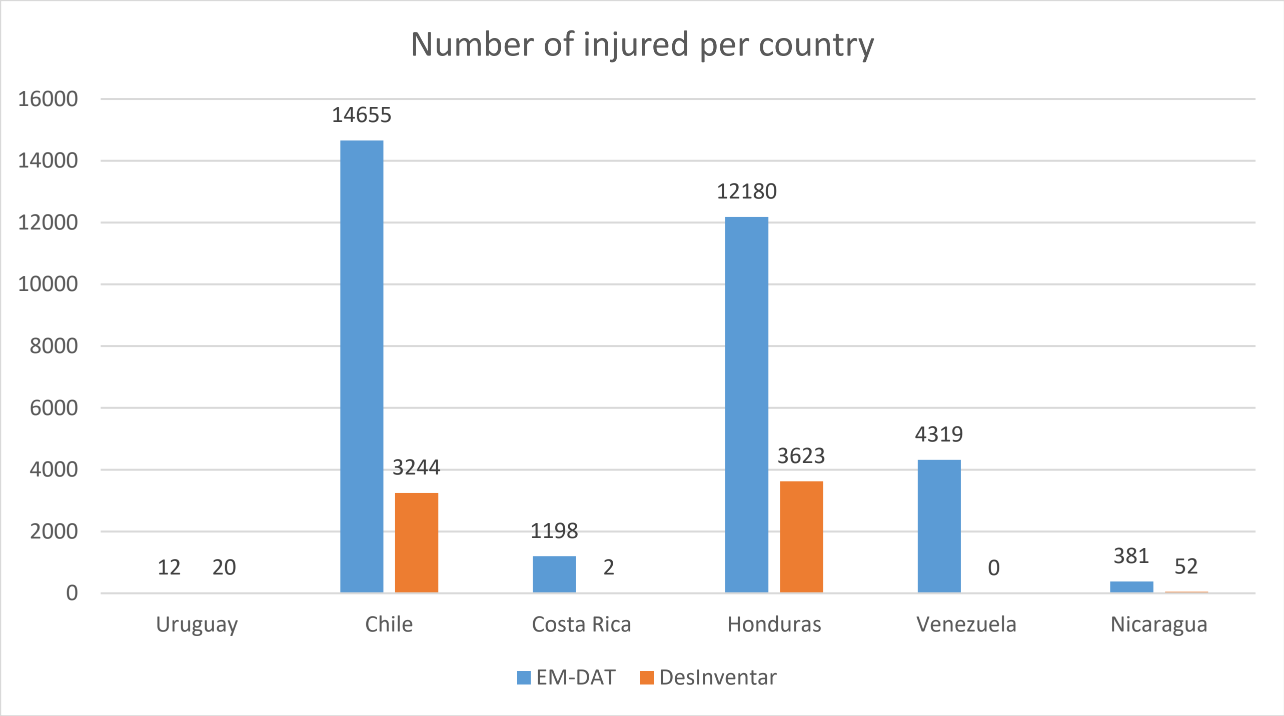

Figure 13 Number of injured per country (matched)

Similar to the indicator 'deaths', the indicator 'injured' also presents a very high number of missing data in both databases. For more than two thirds of the events registered on EM-DAT (71%) and DesInventar (82%), there is no information about the number of people injured during an event. These very high percentages of missing data explain why in Figure 13 there are zero injured people in Venezuela for DesInventar. Missing data have been calculated only considering common events.

4.5 Affected

Figure 14 and Figure 15 show the number of people affected per year in EM-DAT and DesInventar. Once again, only the matched events were considered. Therefore, the numbers should be the same or very close to each other. As already observed for the previous indicators, EM-DAT consistently reports a higher number of people affected. 2010 is the only year where the data reported from the two databases is comparable.

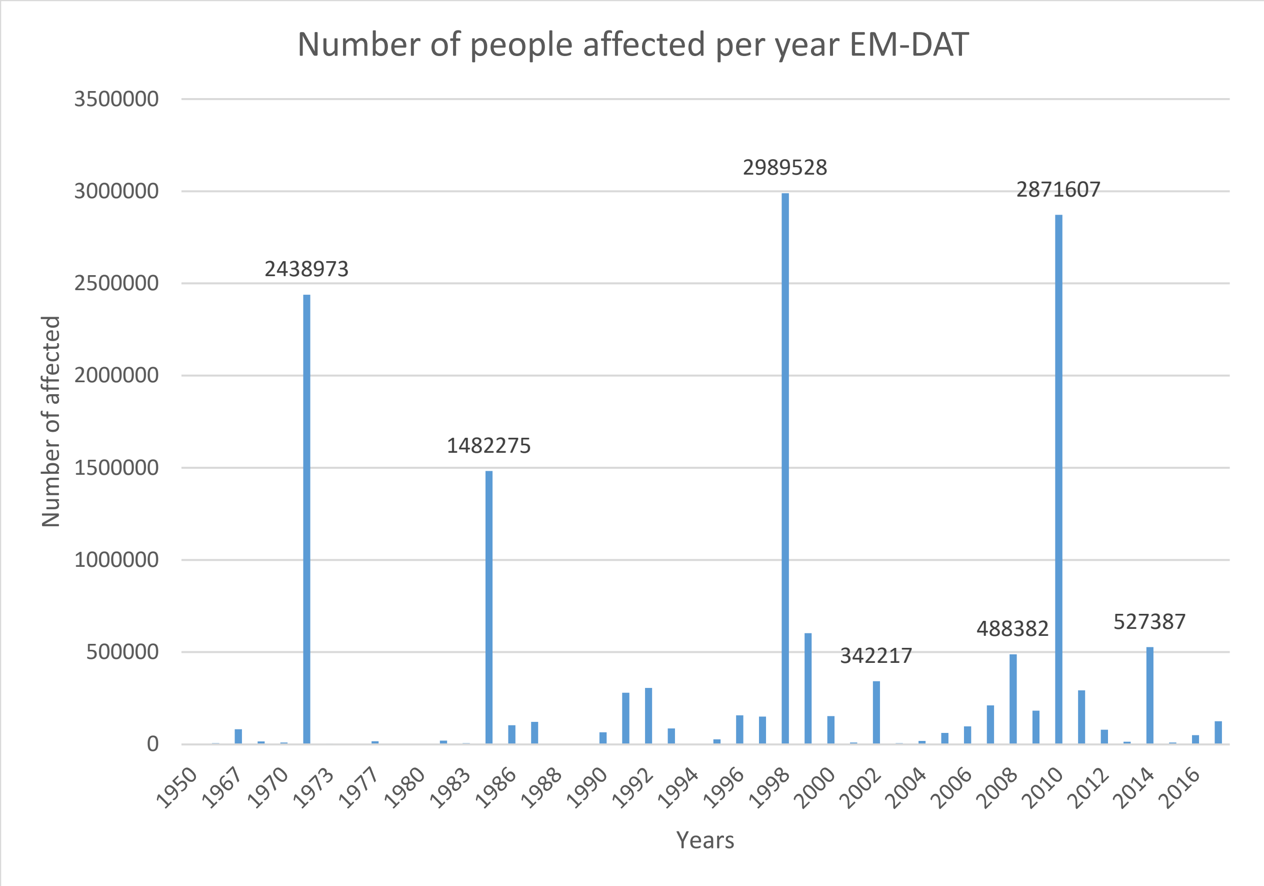

Figure 14 Number of people affected per year EM-DAT (matched events)

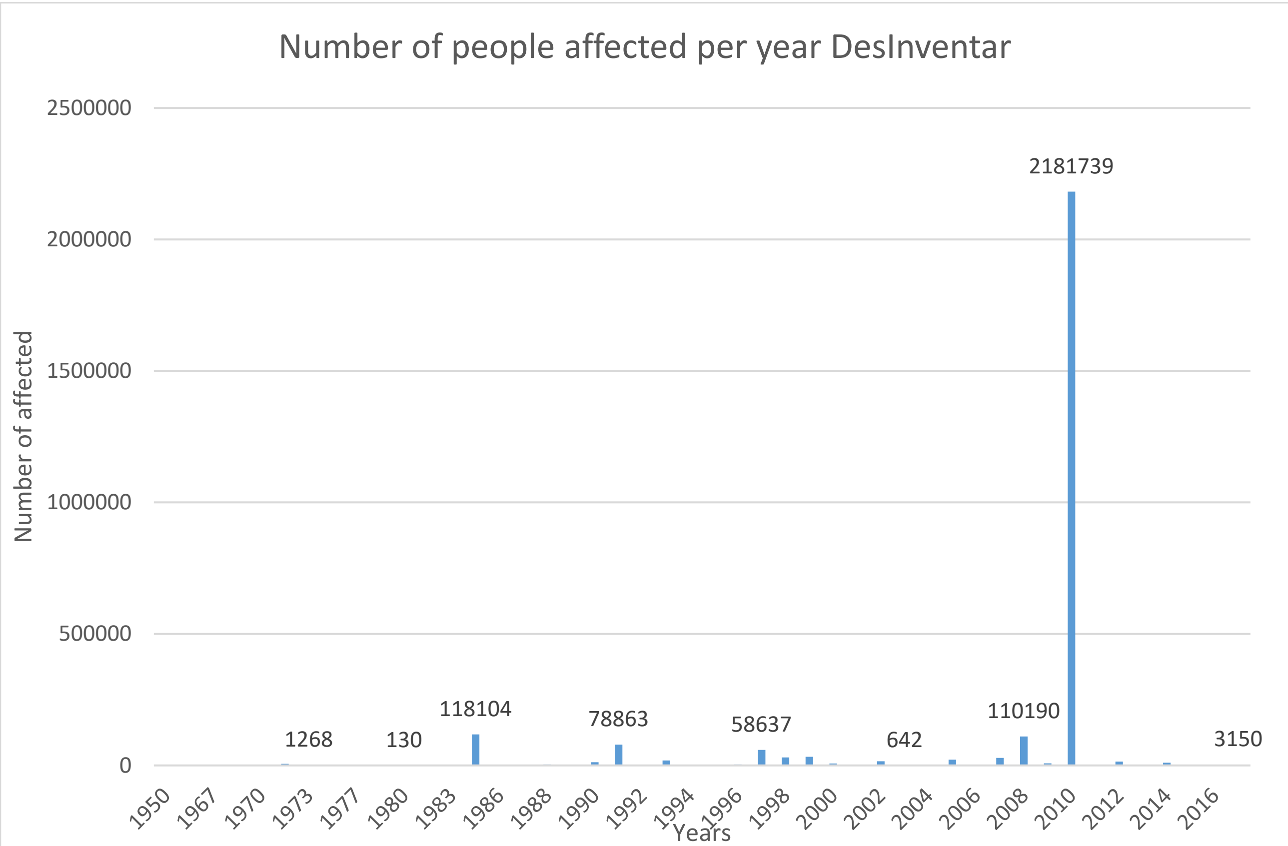

Figure 15 Number of people affected per year DesInventar (matched events)

Figure 16 shows the number of affected people per country. It gives additional confirmation that EM-DAT constantly reports a higher number of people affected.

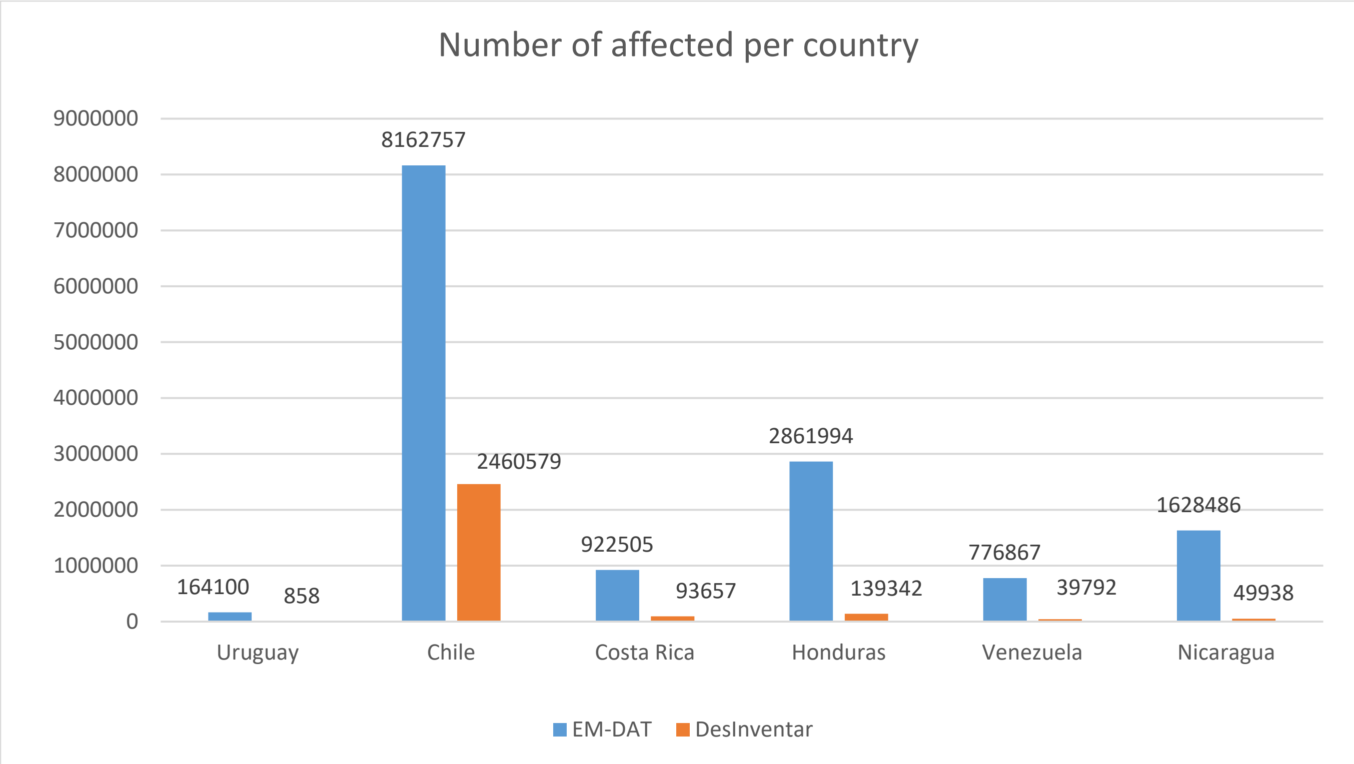

Figure 16 Number of injured people per country

The number of missing data for 'total affected' (EM-DAT) and 'directly affected' (DesInventar) is lower if compared with the previous results. Only 9% of the data are missing in EM-DAT and 38% in DesInventar. EM-DAT constantly reports a lower number of missing data, and this is part of the reason why there are big discrepancies in the graphs showing the number of affected per year or per country. It appears that EM-DAT reports much higher numbers of affected for the same events, but this could be partially due to a lower percentage of missing data in the database. As for the other indicators, these percentages have been calculated only using common events.

4.6 Comparison of deaths/injured/affected for complete events

Table 9 compares the data reported by DesInventar and EM-DAT for each indicator only considering comparable entries between matched events. Among the 159 events that were found to be a match, 52 events exhibit complete data for at least one indicator. Number of deaths is the most complete one, followed by affected and injured.

In almost all those cases where there is a difference in the recorded estimates, EM-DAT reports higher numbers than DesInventar. In a few instances the difference is very small, with EM-DAT having one or two more deaths/injured/affected, but in most of the cases they report completely different information.

For the indicator 'deaths' out of the 51 events (one has been left out due to missing data), 10 have the exact same number. For the indicator 'injured' out of the 18 comparable events 1 reports the same estimate and for the indicator 'affected' out of the 44 comparable events none report the same number.

Table 9 Comparison of deaths/injured/affected for complete matching events

Country	Disaster type	Year	Deaths		Injured		Affected	
			Des-Inventar	EM-DAT	Des-Inventar	EM-DAT	Des-Inventar	EM-DAT
Uruguay	Flood	1998	1	1	1	NA	NA	9300
Uruguay	Storm	2005	0	7	6	12	120	NA
Uruguay	Flood	1998	1	1	1	NA	NA	9300
Chile	Earthquake	1971	78	85	373	451	2784	2348973
Chile	Earthquake	1983	4	4	6	24	620	1524
Chile	Earthquake	1985	2	180	0	2483	0	1482275
Chile	Earthquake	1987	4	5	367	112	1094	5112
Chile	Earthquake	1995	NA	3	50	58	600	1833
Chile	Earthquake	1997	8	8	19	98	15360	53098
Chile	Earthquake	2005	5	11	107	182	3816	27645
Chile	Earthquake	2007	2	2	130	155	16221	25155
Chile	Earthquake	2010	21	562	117	10334	19176	2671556
Chile	Flood	1986	1	23	NA	NA	420	54118
Chile	Flood	2002	7	14	NA	NA	320	221842
Chile	Flood	2006	1	18	NA	NA	NA	95862
Chile	Landslide	1979	25	30	NA	NA	NA	NA
Chile	Landslide	1991	93	141	715	140	0	82811

Country	Disaster type	Year	Deaths		Injured		Affected	
			Des-Inventar	EM-DAT	Des-Inventar	EM-DAT	Des-Inventar	EM-DAT
Chile	Wildfire	2014	15	12	500	500	10000	11000
Costa Rica	Earthquake	1973	10	21	NA	98	1332	3745
Costa Rica	Earthquake	1983	1	2	NA	60	582	5060
Costa Rica	Earthquake	1991	20	47	NA	199	12972	10419
Costa Rica	Flood	1980	4	1	NA	NA	130	1350
Costa Rica	Flood	1991	3	1	NA	21	2238	185021
Costa Rica	Flood	1996	3	6	NA	NA	90	20000
Costa Rica	Flood	2002	2	10	NA	40	0	75040
Costa Rica	Flood	2005	4	4	NA	NA	0	2143
Costa Rica	Flood	2005	1	1	2	NA	4	855
Costa Rica	Flood	2007	2	19	NA	NA	211	12000
Costa Rica	Flood	2010	1	24	NA	NA	10068	3000
Costa Rica	Volcanic Activity	1968	78	87	NA	NA	NA	15671
Honduras	Earthquake	2009	8	7	0	136	NA	50136
Honduras	Flood	1988	2	15	NA	NA	3500	2125
Honduras	Flood	1993	83	374	NA	NA	0	15000
Honduras	Flood	2002	7	10	NA	NA	0	969
Honduras	Flood	2006	14	4	3000	NA	NA	1500
Honduras	Flood	2008	2	67	5	7	200	313357
Honduras	Flood	2011	580	33	NA	NA	2334	69798
Nicaragua	Earthquake	2000	6	7	22	42	0	7477
Nicaragua	Flood	2007	5	10	NA	NA	5	24000
Nicaragua	Flood	2008	7	13	NA	NA	5	3525
Nicaragua	Flood	2010	3	66	NA	NA	204	71000
Nicaragua	Flood	2011	2	17	NA	18	0	143018
Nicaragua	Flood	2013	3	27	NA	NA	0	14149
Nicaragua	Landslide	2004	30	29	NA	18	2274	5769
Nicaragua	Storm	1998	45	3332	30	228	30	868228

Country	Disaster type	Year	Deaths		Injured		Affected	
			Des-Inventar	EM-DAT	Des-Inventar	EM-DAT	Des-Inventar	EM-DAT
Nicaragua	Storm	2000	1	1	NA	NA	140	210
Venezuela	Flood	1997	2	3	NA	NA	0	18000
Venezuela	Flood	1999	0	30000	NA	2700	0	483635
Venezuela	Flood	2004	6	35	NA	NA	NA	4000
Venezuela	Flood	2005	0	76	NA	42	0	25042
Venezuela	Flood	2005	3	3	NA	NA	0	NA
Venezuela	Flood	2008	2	8	NA	NA	284	1500
Venezuela	Flood	2011	8	8	NA	NA	200	2000

4.7 Source comparison

To understand if EM-DAT is over-reporting damages or if DesInventar is under-reporting I selected two events and analysed what is recorded on different media sources.

The first event I selected was the earthquake in Chile on February 27, 2010. It was an 8.8 magnitude earthquake that struck off the coast of south-central Chile, causing extensive damage on land and generating a tsunami that destroyed several coastal areas of the country (ECHO, 2010). Both EM-DAT and DesInventar include the event in their databases. While EM-DAT also states that there is a tsunami connected to the earthquake, DesInventar treats them as two completely separate events. According to several sources, the number of deaths from the earthquake and tsunami combined varies between 500 and 528 (European Commission, 2010; Rafferty & Pallardy, 2023; ECHO, 2010; Latercera, 2010). DesInventar reports 660 deaths for both the earthquake and tsunami despite their source reporting 528, while EM-DAT reports 562 deaths. Knowing more about DesInventar source collection and validation process would help to understand why they report 132 more deaths than those from their official source. Nevertheless, in this case, the biggest difference is in the number of injured. While DesInventar recorded 117 injured, EM-DAT recorded 10344. According to different sources, the minimum estimate is 500 people, and the journal directly linked to DesInventar does not provide any estimate (European Commission, 2010; ECHO, 2010).

Another example of the large discrepancies between the two databases and between the databases and the media is Hurricane Mitch which devastated Honduras and Nicaragua in 1998. Only focusing on Nicaragua, EM-DAT's estimate of 3332 deaths is closer to the media's estimate with reported numbers varying between 3000 and 3800 deaths (Britannica, 2023; U.S. Geological Survey, 2002; La Nacion, 1988). DesInventar only reports 45 deaths, which is considerably lower than the other estimates. In general, the big difference between EM-DAT and DesInventar can also be due to a large amount of missing data in both databases. For the number of deaths, 27% of EM-DAT’s and 59% of DesInventar’s data is missing.

5 Discussion

In this thesis I have been looking at disaster loss accounting databases, to understand if they are reliable in measuring the impact of extreme weather events (Research question 1) and what are their current limitations (Research question 2). As shown in the results section, the data is extremely dissimilar, with EM-DAT consistently reporting higher numbers of deaths, injured, or affected. Ideally, since only common events have been considered, results from the two databases should have been similar to each other to confirm their validity. This would have allowed them to be used interchangeably and to fill the data gaps, but the end result was different from what was expected.

Starting from the volume of data analysed, EM DAT has 17153 less entries than DesInventar for the same time frame and disaster indicators. The difference in the number of records could be due to various reasons, such as the scope of the databases, their sources of information, and the methodology used to collect and validate the data. It is assumed that they both aim to be as complete as possible, but this objective is not specifically stated. Each database clearly explains its entry criteria and which sources are used (Table 1), but it was not possible to find any information about how data are collected and validated. One key difference regarding the sources is that DesInventar, differently from EM-DAT, provides a specific source for every entry. They state that common sources of information, ordered by priority level, are: files created by official emergency management agencies, official sectorial institutions such as ministries, archives of relief aid organizations, academic and scientific journals, and finally newspaper articles (UNDRR, n.d.). All the data analysed in this study, with few exceptions, come from local newspapers, which according to DesInventar's priority list should be the last resort. Nevertheless, newspapers and media articles often become the primary source of information because small disasters are not reported by any other source (UNDRR, n.d.). The abundance of sources available to use permits the researchers to compare between multiple insights and account for over or under estimations and historical information can be obtained for countries where no agencies were in charge of the emergency (UNDRR, n.d.). According to UNDRR (n.d.), inventories only using media sources are reliable and usually as accurate as those created by official sources. Nevertheless, it is essential to acknowledge that the majority of reporting sources have private interests, and data may be impacted by socio-political issues or by the personal view of the researcher comparing the different news sources (ibid.).

Moving to the temporal coverage of events, both databases can trace events back to 1900, but the number of recorded events per year increased starting from 1971. This could mean that a higher number of sources becomes available and that there is an increased interest in measuring disaster effects. Nevertheless, both databases have specific definitions for disaster events as well as for their indicators. The EM-DAT database was established in 1988 and according to their glossary, their definitions come from different sources such as the World Meteorological Organisation (WMO) and internal documents such as a working paper on Disaster Category Classification, Peril Terminology for Operational Purposes from 2009 and a

Peril Classification and Hazard Glossary from 2014. DesInventar instead, was established in 1994 and its definitions follow those provided by the 2015 Sendai Framework (UNISDR, 2019). Both databases were created in the late 1900s, and report data starting from the early 1900s, but they use recently established indicators and definitions. While it may be easier to report the number of deaths, other definitions such as those used for affected or injured evolved through time and are today different from those that were used in 1971. I am therefore wondering how they accounted for this fact, and if data older than 2009 for EM-DAT and 2015 for DesInventar follow different definitions that do not match with the current ones.

With the temporal frame still in mind, DesInventar constantly reports a higher number of events per year compared with EM-DAT. This is due to DesInventar's less restrictive entry criteria (Table 1) and to the different reporting frameworks. While DesInventar only needs one human loss or one dollar in economic losses to include a disaster in the database, EM-DAT will only consider disaster events with ten or more fatalities, at least one hundred people affected, the declaration of the emergency state or a request for internal assistance (UNDRR, n.d.; CRED, n.d.). Moreover, EM-DAT reports the cumulative damage of an event, specifying the start and end date, DesInventar reports the damages separately, registering a new entry for each day. This is why DesInventar reports more events per year than EM-DAT. The number of single entries reported by DesInventar varies according to each disaster. Nevertheless, I noticed that splitting a same event into more days leaves space to possible mistakes and missing data. It is not clear how is DesInventar able to know exactly how many people died, are injured or affected each day. Specifically, because most of the sources tend to report the cumulative damage of an event. Moreover, it is very often the case that several entries are registered but present no data.

When analysing the indicators for the matched disasters I decided to add together all the entries for the same event on DesInventar to translate them in a format similar to the one used by EM-DAT. This has been done to account for EM-DAT's higher per-event damages and allow a more equal comparison of the indicators. Nevertheless, EM-DAT is still reporting much higher damages for every indicator (Table 9). To understand if one of the databases is over-reporting or under-reporting, I decided to compare their data with what is reported by media and official sources. As explained in the methodology the two selected events are the 2010 earthquake in Chile and the 1998 Hurricane Mitch in Nicaragua. In both cases, EM-DAT and DesInventar often report much lower or higher estimates than their sources. All the sources I analysed provide very similar data and I could not find any estimates similar to the ones provided by EM-DAT and DesInventar. If both databases claim to take their data from journals, government agencies, and academic institutions, it does not seem like they accounted for the much lower or higher estimates reported on them. For example, in the case of the Chile earthquake different sources report that the minimum number of injured is 500 people but DesInventar recoded 117 injured and EM-DAT 10344. Even if 500 people injured is the minimum estimate, it is difficult to understand how the database could arrive at 10344 as the number of injured people or that it could be much lower and drop down to 117. Moreover, both databases have a very similar definition of the indicator 'injured'. Injured are all those people whose health has been affected by physical injuries, trauma, or illness as a direct result of a disaster (CRED, n.d.; UNISDR, 2019). Even if the sources I have been consulting have a different definition, then how and why is there such a big difference between the number reported by EM-DAT and the one reported by DesInventar. Another factor that increases the reporting differences between the two databases is the large quantity of missing data. Overall, DesInventar has a higher percentage of missing data than EM-DAT due to its system of reporting damages separately. This contributes to the lower estimates for the same disaster events.

The high percentage of missing data in both databases suggests that, despite technological advancements in disaster surveillance and data collection, there are weaknesses in the current data quality methods (Jones et al., 2022). Between the indicators analysed, 'injured' presents the highest percentage of missing data with 82% for DesInventar and 71% for EM-DAT. This means that data are only present in 18% and 29% of cases respectively. These high percentages of missing data make it very difficult to apply the three conceptual models from De Groeve et al., (2013) discussed in the conceptual framework in Chapter 2. Disaster forensics and risk modelling are strongly dependent on loss accounting. If information is not recorded or available, then it is impossible to examine the progression of a disaster by examining its main causes (disaster forensics) as well as using risk evaluation or prediction techniques (risk modelling) (ibid.). Moreover, for this analysis it increases the difficulties in comparing the differences between the databases increases. In most of the cases, data for matched disaster events for the same indicator are present only in one of the two databases.

Another aim of this analysis was to investigate if the GDP of a country has an impact on the quality of the databases. As shown in Table 8, for the countries analysed, GDP does not seem to play a role in the number of missing data. This is also in part due to the databases' different management systems. While for EM-DAT, CRED is responsible for collecting information and keeping the database updated, for DesInventar, each country has a different owner such as government bodies, NGOs, and research institutions (Moriyama et al., 2018). As previously stated, both databases do not directly collect their own data, but they mainly rely on secondary sources such as official emergency management agencies, official sectorial institutions, academic and scientific journals, newspapers, and articles (UNDRR, n.d.). The quality of primary data can be influenced by the countries' resources, but then the completeness of the database depends on the willingness, capabilities, and internal resources of the database's responsible organisation. It is difficult to know to what extent missing data is due to the unavailability of information or poor management from database's owners. Further studies are needed to investigate the relationship between the GDP of a country and their data collection methods and resources. Nevertheless, in this study no correlation has been found between low GDP and higher number of missing data.

Since GDP does not impact the number of missing data, I wanted to understand if it plays a role in the volume of data collected. Countries with a higher GDP per capita may have more resources and therefore better data collection methods. This may give the impression that some countries are more subjected to disasters simply due to the fact that there is more data collected. This may also result in a higher devolvement of resources and programs for these specific countries, while others with worse reporting methods are left out. As seen in Table *5* which shows the volume of data per country for each database, having a higher GDP does not affect the number of events reported in the databases. Uruguay is the country with the highest GDP in 2021, but this does not automatically translate into a higher number of recorded events.

5.1 Are disaster loss accounting databases reliable in measuring disaster impacts?

Going back to the first research question "Are disaster loss accounting databases reliable in measuring disaster impacts", the answer is not yet. Both databases cover an extensive range of disaster categories and a comprehensive temporal frame, nevertheless, there is no clarity over how data are collected, validated, and compared between different sources. As shown from the comparison of the database reporting of the 2010 Chile earthquake and the 1998 hurricane in Nicaragua with what is reported from online media, for some indicators there are large information discrepancies. For these two events, different media articles tend to report similar information without very big discrepancies between each other, but EM-DAT and DesInventar report very different estimates and in the case of DesInventar they are even different from the sources they cited on their database. I assume this is not always the case, for example, EM-DAT's number of deaths for Hurricane Mitch is in the range of what is reported by the media, but in order to be able to use these data to produce reliable estimates, assess potential risks for future disasters, prevent losses and to monitor the effect of disasters, the source has to be consistently reliable, not only in some specific cases. Moreover, by just comparing the two databases for the same disaster events and indicators, they either report very different estimates or data are missing. The high percentage of missing data is another factor decreasing the reliability of both databases. As shown in Table 8, especially for DesInventar, more than half of the data for selected indicators are not available. This means that when conducting analyses, it is fundamental to account for the high presence of missing data using case specific techniques (Jones et al., 2022). However, according to Jones et al., 2022, these methods can often compromise the precision and reliability of the analysis. Finally, the last aspect decreasing the reliability of the two databases is the difficulty in comparing the definitions of the indicators used. Both databases have their own definition for each indicator, but when taking data from media sources, NGOs, or scientific journals, how do they ensure that they have used the same definition? While for some indicators such as 'number of deaths' there are no big differences in definitions, for others such as 'affected' the situation is different. Table 3 reports all the definitions for the indicators selected in this study. Before starting my analysis, I examined all the definitions to assess if the indicators were comparable or not. Nevertheless, I am aware that this has been done according to my personal view. Even trying to be objective and unbiased, results could change according to the background, biases, and understanding of the person analysing them. Moreover, some definitions such as the one for 'affected' are very ambitious and would require an explanation of how the databases plan to account for all the aspects they list in them. For example, DesInventar defines 'affected' as "People who have suffered injury, illness or other health effects; who were evacuated, displaced, relocated; or have suffered direct damage to their livelihoods, economic, physical, social, cultural and environmental assets" (UNISDR, 2019, p.19). While it may be easier to account for injuries, health effects, displacement, and relocation, it is not clear how they intend to account for physical, social, cultural, and environmental assets damages and how they verify if these aspects are also considered in the definition of 'affected' used by their sources. The ambiguity of the definition is also reflected by the fact that in Table 9, there are no entries reporting the exact same estimate for this indicator.

5.2 What are the current limitations of existing disaster loss accounting databases?

Moving to the second research question "What are the current limitations of existing disaster loss accounting databases", this is a list of the limitations I have found during this analysis:

- Little or no use of GLIDE numbers. Few entries on EM-DAT and no entries on DesInventar have a GLIDE number. This increases the possibilities of double counting events, of mismatching them and in general does not allow to quickly compare the same event between the two databases.
- High presence of missing data. The very high percentages of missing data is a limitation in accessing information and conducting analyses. Very often it was not possible to match events or compare indicators. Jones et al., 2022 show several techniques to account for this problem, but they are only applicable if analysing the databases in their entirety. When information on a specific event is needed it is very likely that it will be missing. For example, when I selected two disaster events to compare them with what is reported by the media, I was limited in my choice. Many events were impossible to analyse because of data missing on one of the two databases.
- Generic descriptions of the data sources. Both databases only have generic descriptions of their sources. While DesInventar provides the name of the newspaper or organization from which the data are taken, EM-DAT does not give any detailed information. Moreover, if different sources are used there is no transparency on how information is validated and merged.
- Absence of shared terminology and indicators. There is no shared terminology across disaster loss accounting databases. EM-DAT and DesInventar use different definitions for the same indicators, this increases confusion and can result in a less accurate and more complicated comparison. According to the European Commission (2015), indicators' definitions should be precise, comprehensive, measurable, and practical. This means that loss indicators should have precise definitions to avoid double counting, all classes of affected should be included, they must be measured by private organizations, media or assessed in the field and finally, they must be in line with existing practices and with what is usually recorded (ibid.). From what I could see in this analysis the definitions are not always mutually exclusive. For example, people who are injured also fall under the 'affected' definition. The human indicators are quite comprehensive, with DesInventar

also accounting for the long-term psychological effects of a disaster. Unfortunately, they do not specify when consequences start being considered as long-term and in the case of intangible damages, it becomes very difficult to measure them. Finally, DesInventar has a broad range of very specific indicators such as ‘livelihoods affected’ or ‘agricultural assets affected’ that differ between countries, are not clearly defined, and that in general present very little or no data. This means that they are not in line with existing practices and are not usually recorded in the field.

- No cohesive language in DesInventar. The database is publicly accessible, and the information should be reported in English to be understandable and used by a wider public. Most of the indicators and names in the database are in English but there are some that have been translated into Spanish (the local language). The use of two different languages may cause misunderstandings and confusion, especially when the same indicator or disaster event is reported twice in both English and Spanish and the definitions on the glossary are only in English.
- Underrepresentation and difficulties in measuring the impact of slow onset disasters. EM-DAT is only limited to droughts as slow onset hazards, while DesInventar also includes coastline changes and biodiversity decline (Gall, 2015). To capture the adverse effects of slow onset events, new hazard types should be included in the databases. The main challenge would be that the focus of both databases is to capture the direct impacts after a disaster, but slow onset disasters tend to have limited direct impact, and the consequences are only seen after years have passed (Zaidi, 2018). Estimating indirect losses for every loss occurrence would be methodologically challenging and much more difficult than recording the consequences of a sudden onset disaster (Gall, 2015). A new recording system keeping into account cause-effect relationships would be needed.
- Limitations in EM-DAT’s data availability on low intensity disasters. Due to CRED’s stringent entry criteria, no small-scale disasters are included in the EM-DAT database (Jones et al., 2022). According to the European commission (2022) the combined economic, social and environmental costs of small-scale disasters can be higher if compared to high impact and low frequency disasters occurring over the same time period. Moreover, they can also reveal local development and planning issues that can explain higher levels of vulnerability to more large scale events (ibid.)
- Collecting data during and after a disaster is not a priority (European Commission, 2021). If there are no previously established strategies and procedures to collect data among the stakeholders involved, this will not be prioritized (ibid.).
- No or insufficient reporting of secondary disasters. If for example, an earthquake generates a tsunami wave, DesInventar will record it as two separate independent events, while EM-DAT will only indicate that the earthquake produced a tsunami. Since EM-DAT uses an internal code system it would be helpful if it could provide the code of the connected disaster. This would make the analysis of damages much easier and would decrease the possibility of selecting the wrong secondary disaster.

- Treating disasters as episodic events with temporal, geographical, and statistical boundaries restrict the potential of capturing the wide sphere of consequences produced by a disaster (Zaidi, 2018). Delimiting the time and location of a disaster, as well as establishing a limited set of indicators, are boundaries necessary for a more efficient collection of data but can oversimplify the event and only evaluate it according to measurable information.

Disaster loss accounting databases have a great potential, but they also present a large number of limitations that restrict their use. According to CRED et al., (2022), over the last 25 years (1996-2021), the use of EM-DAT has steadily increased. In 2021, 59 empirical papers across all scientific research disciplines used EM-DAT as a primary or secondary source (ibid.). Users go from country reports to international organisations such as WHO and OCHA (ADCR, 2005; WHO, 2020, OCHA, 2020). No similar statistics are available for DesInventar, but it is often defined as one of the key databases for disaster loss accounting (UNDRR et al., 2022). Their increasing use is a sign of a growing interest in data-driven disaster research (CRED et al., 2022). This has been driven by growing media attention and international agreements to lower disaster risk and increase disaster resilience such as the COP summits, the 2005–2015 Hyogo Framework, and the 2015– 2030 Sendai Framework (ibid.). Nevertheless, it is important to ensure that their increasing use and reliability go together.

The next steps toward a more reliable disaster loss accounting system should be to clearly define the scope and purpose of the system that includes hazards and losses, geographic coverage, and target audience (European Commission, 2015). Secondly, hazard and loss indicators should have consistent definitions and measuring standards (ibid.). Procedures should also be established for managing and collecting the data, to ensure accountability of sources, quality control measures, and mechanisms for data sharing and privacy protection (Migliorini, 2019). Methodologies and procedures should be standardized, transparent and replicable for estimating disaster losses, and support capacity building efforts to reinforce the skills and knowledge of those involved in the process such as data collectors, analysts, and decision makers (Cuthbertson et al., 2021). Finally, the system must include a procedure for monitoring and evaluating performance over time, including its ability to satisfy stakeholders' needs and the impact on policy and decision-making (ibid.). Considering these factors is a first step in the direction of a standardized disaster loss accounting system, which will eventually promote more effective disaster risk management and reduction by increasing the accuracy, comparability, and utility of data on catastrophe losses.

5.3 Limitations of the study

This thesis provides a comparison of the two most used disaster loss accounting databases to understand their effectiveness in measuring the impact of disasters and extreme weather events and what are their current limitations. Due to time constraints, the analysis was only done on a sample size of six Latin American countries. The obtained results are expected to be generalizable to the entire databases, but there may be differences in the estimates provided in the results section if, for example, different or more countries were selected. Nevertheless, similar studies focusing on different or more countries had very similar results to the ones obtained in this thesis (Jones et al., 2022; Mazhin et al., 2021; Panwar & Sen, 2019). Similarly, due to limited accessibility, I could only compare two disaster databases. As Sigma and NatCatSERVICE are owned by two private insurance companies, I would expect them to be updated more frequently, have a lower number of missing data and provide more precise estimates than EM-DAT and DesInventar.

Once the sample of countries was selected, the entire data matching and analysis was done manually without the use of any statistical program. Full attention was paid to details and the events were controlled several times before defining them as matching; however, it is still possible that some of the disasters were incorrectly matched or left out. Moreover, the very high number of missing data especially for date and location, prevented many disasters from being matched and analysed.

Disaster events have then been compared on the basis of selected loss indicators with analogous definitions. Unfortunately, there is no standard system to assess the definitions' similarity or no list of corresponding definitions across EM-DAT and DesInventar. The selected indicators have been categorized as similar according to my understanding and to what has been done in previous studies (Jones et al., 2022; Mazhin et al., 2021; Panwar & Sen, 2019). It is possible that another person with a diverse background and understanding may have matched them differently. The same reasoning applies to disaster event definitions, especially when they are translated into the local language. Nevertheless, besides these possible subjective interpretations, the obtained results conform to those obtained in previous studies using a similar methodology (Jones et al., 2022; Mazhin et al., 2021; Panwar & Sen, 2019).

Finally, low data quality affects the reliability of the estimates provided in the results section, especially regarding the temporal frame and the number of events per year for each indicator. The big differences between EM-DAT and DesInventar give no unique answer to the number of deaths, injured, or affected per year, or country. Nevertheless, my aim was not to analyse how many people die per year due to a specific event but to compare the same information coming from two different databases and assess if they are reliable and if their data can be used for further analyses.

6 Conclusions

The collection of reliable and comparable data can be a crucial first step in improving risk assessment, preparedness, and management process (European Commission, 2013). Different global strategies for disaster risk reduction and management can be used depending on the priorities of the actors involved (Migliorini et al., 2019). These actions may include establishing disaster's impacts, disseminating effective risk reduction measures tools, outlining socio-economic processes to encourage the involvement of new resources, and promoting preparedness (ibid.). In all these processes disaster loss data can be the base upon which decisions are taken. They can be used to examine the progression of a disaster and its root causes and enhance risk evaluation and prediction techniques thanks to a greater understanding of vulnerabilities and specific sectors' needs (Masys, 2016; De Groeve et al., 2013).

Nevertheless, the power and usefulness of disaster loss data depend on their quality and reliability. The use of poor-quality data will produce unreliable results that can lead to false prediction, misuse of resources, and in general not contribute to the improvement of risk assessment, preparedness, and management processes. Starting from existing data collection practices I compared two of the most used disaster loss accounting databases, EM-DAT and DesInventar, to assess if they are reliable in measuring disaster impacts and to identify their current limitations. Both databases are comprehensive in terms of disaster categories and temporal frames, but it is not clear how data are collected, validated, and compared between different sources. When selecting single events common across both databases, there are very big differences between disaster indicators making it difficult to understand which ones are the correct estimates. If for the same disaster event and indicator EM-DAT and DesInventar report completely different data, then how can we choose which ones are the most reliable estimates? To answer this question, I tried to consult media and online journals that are part of the possible sources used from the databases, but large information discrepancies are still present. In addition, the very high number of missing data is another factor decreasing the reliability of both databases. During analyses, it is fundamental to account for their presence using specific techniques, but according to Jones et al., 2022, these methods can often compromise the precision and reliability of the analysis and are only applicable if conducting a study at a country, event, or temporal level. If the databases are used to look for information on a single specific event there are high possibilities that the information will not be available.

Disaster loss accounting databases in their current state are far from perfect and present several limitations. The main drawbacks identified in this study are little or no use of GLIDE numbers, generic description of their sources, high numbers of missing data, absence of a shared terminology, underrepresentation of slow onset hazards and low intensity disasters and insufficient reporting of secondary disasters. All these drawbacks can be attributed both to the lack of commonly agreed standards and procedures, as well as, by the fact that the database owners do not directly interact with them as end users. In the case of EM-DAT and DesInventar the owners are not the final user of the databases and therefore they are less aware of their state and difficulties. I would assume that Sigma and NatCatSERVICE, being owned by private insurance companies that also use their own database, are in a better state.

Future research can contribute to the establishment of common disaster indicators' definitions and measurement criteria, establish quality control measures to guarantee source accountability and establish a system to enable knowledge sharing between data collectors, analysts and decisionmakers (Migliorini, 2019; Cuthbertson et al., 2021). Current limitations should not be considered as an incentive to stop using the databases, but as an encouragement to improve them and use them at their full potential.

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