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D4.3

Report on Novel Methods for Detecting Empirical Evidence of Dynamics & Feedbacks of Risk Drivers

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D4.3/Report on Novel Methods for Detecting Empirical Evidence of Dynamics & Feedbacks of Risk Drivers

Lead by VUA
Authored by Marleen de Ruiter (VUA), Wiebke Jäger (VUA), Sophie Buijs (VUA), Timothy Tiggeloven (VUA), Tristian Stolte (VUA), Kelley De Polt (MPG), Andrea Critto (CMCC), Silvia Torresan (CMCC), Margherita Maraschini (CMCC), Marcello Sano (CMCC) Davide Mauro Ferrario (CMCC), James Daniell (Risklayer), Bijan Khazai (Risklayer), Robert Sakic Troglic (IIASA)
Reviewed by Philip Ward (VUA), Julia Crummy (BGS)

Abstract

This report (Deliverable 4.3) provides a comprehensive overview of innovative methods that have been identified to assess multi-hazard risk dynamics. These methods consider the spatial and temporal dynamics in exposure and vulnerability resulting from interactions between multiple hazards and disaster risk reduction measures. The subsequent research supports risk managers in understanding risk dynamics and the effects of DRR measures, enabling decision makers to be better prepared for and recover from multi-hazard risk events.

The report discusses existing databases and vulnerability statistics, as well as novel methods and data sources, highlighting opportunities and challenges in using these methods and data sources. Notable methods include developing a comprehensive vulnerability database for urban areas, utilising novel data streams like Google Trends and newspaper articles for understanding impact durations, using night-time light satellite data for recovery pattern analysis, implementing Machine Learning for multi-risk assessment, and employing Disaster Forensic Analysis to learn from past events and the impact of risk reduction measures.

Dissemination level of the document

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Executive summary

This report (Deliverable 4.3) presents a comprehensive overview of innovative methods and data sources that are being employed by MYRIAD-EU to assess risk dynamics and feedbacks between risk components in a multi-hazard risk context. These methods consider the spatial and temporal dynamics in exposure and vulnerability arising from: (1) interactions between multiple hazards; and (2) the implementation of disaster risk reduction (DRR) measures aimed at addressing these hazards. This research supports risk managers to better understand the dynamics of risk and the effects of DRR measures, and it enables decision makers to be better prepared for and recover from multi-hazard risk events.

As more and more people are facing natural hazards worldwide, it has become crucial to broaden our approach from studying one hazard at a time to considering multiple hazards together. This shift helps us understand how these hazards interact with one another—like how one hazard can trigger, amplify, or compound the effects of another. Underpinning this, is a comprehensive risk framework that considers the hazard itself, how exposed we are to it, how vulnerable we are to its effects, and how we respond to it. By understanding these relationships, we can make better decisions to manage the risks of natural hazards in a comprehensive and interconnected way, across different sectors. However, to better understand these relationships and dynamics. To do this, we require novel methods and data sources. This report discusses the current state-of-the art, it presents promising novel methods and data sources that are being, and will be, used by MYRIAD-EU, and discusses challenges and opportunities in using them.

In this deliverable, we highlight the following novel methods and data that we have identified, and we discuss the challenges and opportunities in using them to assess different dynamics of multi-hazard risk:

- The development of a comprehensive database of vulnerability drivers for six different hazards for urban areas.
- Data obtained through novel data streams such as Google Trends and newspaper articles are used to understand impact-relevant durations of extreme events such as heatwaves.
- Nighttime light (NTL) satellite data are used to assess recovery patterns using a statistical difference-in-difference (DiD) analysis.
- Machine Learning is used to analyse multi-risk for historical and future scenarios in the Veneto pilot study.
- Disaster Forensic Analysis and paired-event analysis are used to study past events and learn lessons regarding disaster risk dynamics and the impact of DRR measures.

1 Introduction

1.1 Background

Risk, defined by the UNDRR (2019) as the product of hazard, exposure and vulnerability, is typically assessed and managed from a single hazard perspective, often neglecting spatial and temporal feedbacks between risk elements (Ward et al., 2022; De Ruiter et al., 2020). However, real-world disasters show that there are many dynamics and feedbacks at play that are traditionally not captured by risk models. For example, an earlier disaster can increase vulnerability at the time of a second event. Therefore, the international community (e.g., IPCC 2022, UNDRR 2022) have called upon disaster risk scientists to improve our understanding and modelling capabilities of dynamics and feedbacks of risk and risk elements. MYRIAD-EU's WP4 aims to improve modelling multi-(hazard) risk dynamics and feedbacks. These improved modelling capabilities can in turn can be used to better inform disaster risk reduction (DRR) and adaptation strategies, and to support evidence-based decision-making. To better assess and model these multi-(hazard) risk dynamics, we require methodologies that can capture different aspects of these risk dynamics (Ward et al. 2022). Finally, the assessment of risk dynamics and feedbacks not only requires novel methods but also extensive data.

1.2 Aims and scope

This deliverable aims to report on the methodological developments that have been identified as part of Task 4.1 ("Novel approaches for identifying evidence of dynamics & feedbacks of risk drivers"), which was part of the "Initial design and development step" of the project. The findings from this task will feed into the next step of the project (i.e. "the Iterative Testing & refinement" step); they will be further developed and tested in Task 4.3 to quantifying the dynamics and feedbacks of multi-hazard risk drivers"), they will be used to support the development of the database of empirical evidence of dynamic feedbacks between risk drivers (Task 4.4), and finally they will be incorporated in the software package and user guide for multi-hazard and multi-risk scenario generation (Task 5.4).

In this deliverable, we outline a range of novel approaches, including several statistical and machine learning techniques, and open access data sources, that have been identified for application to detect different aspects of disaster risk dynamics. This report presents and discusses the opportunities and challenges of using these methods and data sources for understanding risk dynamics. Within the MYRIAD-EU project, the identified methods and data sources will be used to detect changes in reported losses and damages due to spatial and temporal dynamics in exposure and vulnerability caused by: (1) interactions between multiple hazards and (2) DRR measures taken to address those hazards. We also discuss how Disaster Forensic Analysis are used to study past events and learn lessons regarding disaster dynamics and the impact of DRR measures.

1.3 Structure of the deliverable

In section 2, we outline the current state-of-the-art and research needs regarding the assessment and modelling of multi-risk dynamics and dynamics of and between components of risk. Section 3 first provides an overview of existing key databases and vulnerability functions statistics that exist at global, EU, national and local scales, and highlight those that have been identified for the assessment of multi-hazard risk dynamics in MYRIAD-EU. We also describe an innovative vulnerability drivers' database, encompassing six distinct hazards, that was developed by MYRIAD-EU. We then discuss various novel methods, including statistical and machine learning techniques, that have been identified for the assessment of different aspects of multi-risk dynamics. Next, we highlight the use of Disaster Forensic Analysis to study past events, offering valuable insights into disaster dynamics and the effectiveness of DRR measures. We also discuss ongoing work on the consecutive occurrence of disasters and waterborne disease outbreaks and next, in section 4, we present our main findings concerning the challenges and opportunities associated with well-established and novel data sources, as well as methods used for detecting risk driver dynamics and feedbacks. We also assess their suitability for use in local case studies. Finally, in section 5 we present our overarching conclusions.

2 State of the art and research needs

2.1 Hazard

The shift from a single-hazard focus within risk assessment and hazards research to a multi-hazard focus is necessitated by the increasing number of people exposed to natural hazards around the world. Shifting this focus to a multi-hazard scope allows for the analysis of different hazard relationships such as triggering, amplifying, compounding, and sequencing (Gill et al., 2022). A further understanding of these relationships allows for more informed disaster risk management that considers multi-(hazard) risks in a multi-sectoral, systemic approach (Ward et al., 2022). In the current literature, natural hazards, and in particular climate extremes, are classified as extreme if the value of one or more characteristics is above (or below) a threshold. These thresholds may differ between different definitions, meaning that hazards with the same name may be classified differently. This difference in classification may then translate into differences in measured impacts or damage (Seneviratne et. Al., 2021). This leads to the need for an analysis scheme to produce comparable single- and multi-hazard assessments across different sectors (Orth et al., 2022). Within MYRIAD-EU, we aim to produce intensity-damage relationships for single- and multi-hazard events to further understand the dynamics between risk drivers. As a first step towards this goal, a workflow for determining impact-relevant durations has been developed and applied to the case of heatwaves in Germany across health and societal attention sectors (De Polt et al., 2023). If we can recommend impact-relevant characteristics of events, such as duration, we can better inform, in a more consistent way, on which characteristics events should be analysed in terms of impact or societal response.

2.2 Exposure and vulnerability

Vulnerability research suffers from a lack of data and conceptual challenges (Formetta & Feyen, 2019; Jurgilevich et al., 2017; Schneiderbauer et al., 2017). It is therefore difficult to measure vulnerability – especially on the social side where it is often not visible or easily quantifiable. Moreover, if we can quantify vulnerability, we usually make use of static data and some general indicators like (the population's) age or poverty (e.g., Rufat et al., 2015). Additional value in vulnerability assessments lies in the description of the pathways through which certain hazards impact people and assets. But to incorporate this into risk assessments, we need information on what actually drives vulnerability, as well as on vulnerability dynamics.

Current research into vulnerability drivers seems to have reached a plateau, as we insufficiently challenge the underlying theories (Kuhlicke et al., 2023). We are therefore at a risk of blindly adopting existing vulnerability indicators for each new risk assessment. This is especially true for larger geographical scales, because the data are less detailed and because vulnerability is a very context-dependent concept (Hinkel, 2011). Moreover, vulnerability from a multi-risk perspective and the dynamics that it brings along have hardly been addressed so far in the scientific literature (de Ruiter & van Loon, 2022). More specifically, vulnerability drivers for one hazard may not apply (in the same way) to another hazard (de Ruiter et al., 2021). In MYRIAD-EU we attempt to move on from the plateau by collecting empirical evidence on drivers of vulnerability for several different hazards (Stolte et al., submitted for publication).

If we know what drives vulnerability, we can move towards addressing the dynamics of vulnerability in a more holistic way. In our research, we have synthesised the current state of knowledge on vulnerability dynamics (Stolte et al., submitted for publication; de Ruiter & van Loon, 2022). Within our research for the MYRIAD-EU project, we have identified three forms of dynamics based on literature and expert knowledge (de Ruiter & van Loon, 2022): (1) time dynamics, which relate to changes in vulnerability drivers over time (e.g. how poverty evolves over time for a country; e.g. de Ruiter et al., 2021), (2) directional dynamics, which describe the link between vulnerability drivers and the impact beyond a linear relationship (e.g. Stolte et al., submitted for publication), and (3) management dynamics, which are about the way in which we deal with vulnerabilities (e.g. Schipper, 2020). Next, we need to find ways to incorporate these dynamics in (multi-)risk assessments. Since our understanding of the dynamics is getting increasingly better, the biggest challenge ahead is obtaining sufficient data. Local scale assessments bring an opportunity to obtain detailed data on an area small enough to comprehend vulnerability dynamics, but such data are not always available or accessible. Therefore, another option is to try to supplement existing data with Machine Learning techniques.

Multi-hazard events pose a significant threat to human communities and infrastructure, and understanding the role of social vulnerability in exacerbating their impacts is essential (Drakes & Tate, 2022). Social vulnerability refers to the unequal distribution of resources, power, and resilience among different social groups, leaving certain populations more susceptible to the consequences of disasters (Bergstrand et al., 2015; Rufat et al., 2015). Disparities in wealth, access to healthcare, education, age, and social support systems contribute to social vulnerability, resulting in differential impacts during multi-hazard events (Drakes & Tate, 2022).

Recent disasters have highlighted the growing complexities associated with disaster risk and the challenges they pose to society. In our paper, we (De Ruiter and Van Loon (2022)) propose a paradigm shift, focusing on the factors that shape dynamic vulnerability. We identify three types of vulnerability dynamics: (1) the underlying dynamics of vulnerability; (2) changes in vulnerability over the course of prolonged disasters; and (3) changes in vulnerability during compounding disasters and societal shocks. We contend that qualitative and model-based approaches hold significant potential for capturing vulnerability dynamics, allowing us to recreate past trends and project future patterns, such as narrative-based approaches, agent-based models, and system dynamic models.

While there are a plethora of methods to assess vulnerability (for an overview, see Douglas 2007, De Ruiter et al., 2017 and Hagenlocher et al. 2019), we identified a large gap in capturing the dynamics of vulnerability in single- and multi-hazard risk assessments (de Ruiter and van Loon, 2022). In this report, we provide an overview of methods and approaches, both quantitative and qualitative, for assessing dynamic vulnerability to various natural hazards in a multi-hazard setting (including hazards such as flooding, droughts, landslides, earthquakes, volcanic eruptions, heatwaves, wildfires, and tsunamis).

2.3 Recovery

Recovery after disaster events is defined as *"The restoring or improving of livelihoods and health, as well as economic, physical, social, cultural, and environmental assets, systems and activities, of a disaster-affected community or society, aligning with the principles of sustainable development and 'build back better', to avoid or reduce future risk."* (UNDRR, 2020). In recent years, scientific studies have been adopting a broadened view of post-disaster recovery, exploring topics such as self-recovery (e.g., Ahmed & Parrack, 2022; Sergeant et al., 2020; Schofield et al., 2019), as well as multi-hazard recovery (e.g., Hariri-Ardebili et al., 2022; Mohammadi et al., 2023).

In a multi-hazard context, the recovery process can be more complex than in a single-hazard context, especially in the case of a consecutive disaster, where two or more disasters occur in succession, with direct impacts that overlap spatially before recovery from the first event is completed (de Ruiter et al., 2020; Mohammadi et al., 2023). Response and recovery after the first disaster can become more demanding or challenging because of the occurrence of a second event (Mohammadi et al., 2023). Rescue teams might physically be hindered in their rescue efforts, like in 2021 in Haiti, where the landfall of tropical storm Grace caused a race against the clock for post-earthquake rescue operations (IFRC, 2021). Moreover, humanitarian personnel and financial resources can get depleted after a first disaster, while societal needs and dependence on humanitarian aid can remain high or become even higher after the second event. On the other hand, successful recovery between events can lower a community's vulnerability to consecutive hazards, for example through the implementation of 'build back better' efforts. While the recovery process after a first disaster can have a large influence on the impact of a second disaster, we still have a poor understanding of multi-hazard recovery. To a large extent, multi-hazard analyses are still restricted to qualitative and semi-quantitative approaches; recovery 10mbrace10g is often still done from a single-hazard perspective; and in multi-hazard risk and impact assessments, recovery dynamics and residual damages are generally not included (de Angeli et al., 2022; Dhulipala et al., 2021; Kong et al., 2019).

There are several recent studies that have taken initial steps to qualitatively understand or assess recovery in a multi hazard context, such as the research by Mohammadi et al. (2023), who have elaborated on multi-hazard recovery as a concept and on the challenges that are involved with multi-risk recovery planning, through a critical review of existing literature and guidelines on disaster recovery. In the studies of Hariri-Ardebili (2020) and Hariri-Ardebili et al. (2022), some generalised conceptual representations of recovery under different multi-hazard scenarios are provided. They adopt a very broad perspective on multi-hazard events by studying the Covid-19 pandemic not only in relation to natural hazards, but also in relation to other complex emergencies like mass protests or military movements. They explore the recovery of the healthcare system after such multi-hazard events in a qualitative manner by analysing several different multi-hazard scenarios (i.e. pandemic + natural hazards and/or complex emergencies).

Other studies have applied a more quantitative approach to study multi-hazard recovery. Dhulipala et al. (2021) have, for instance, developed a generalised post hazard-event systems recovery modelling framework, based on state dependent Markov-type processes, which can be applied to multi-hazard events to simulate multi-hazard recovery curves. They demonstrate the model on a case study, where they simulate a set of multi-hazard recovery curves for 64 houses in a community, which are then averaged to construct multi-hazard community recovery curves. Another study by Kong et al. (2018) has taken a quantitative approach to study multi-hazard infrastructure resilience. In various studies, recovery is analysed under the broader concept of resilience; Mohammadi et al. (2023) note that the ability to recover from a disruptive event is one of the most critical components of overall system resilience and that often recovery indicators have been used to measure the resilience of a system. Kong et al. (2018) observe that with regards to infrastructure resilience, the effects of overlapping, sequential, and related hazards are rarely considered in literature. They develop a quantitative approach to analyse the resilience of interdependent infrastructure networks that are subject to multiple sequential hazards. Through a case-study application of their methodology, they show that multi-hazard resilience is always different from the sum of single-hazard resilience.

While it is important to understand recovery in a multi-hazard context when designing adequate disaster risk management strategies, most multi-hazard research to date has focused on the physical aspects of multi-hazards (Gill & Malamud, 2016; Tilloy et al., 2019), leaving the social aspects relatively understudied (Drakes & Tate, 2022). Moreover, within the socially oriented studies, there is a strong focus on pre-disaster preparedness and mitigation, rather than post-disaster response and recovery (Drakes & Tate, 2022). While some initial advances in the field of multi-hazard recovery have been made in recent years, most studies are either qualitative or semi-qualitative and the quantitative studies that do exist are very localised and specific (i.e., focused on a single system in one location, e.g. only one bridge, or one community). Generalised quantitative observations about how recovery is different or similar after single- and multi-hazard events are still missing. Deeper insights into the general differences between single- and multi-hazard recovery can ultimately help to enhance disaster preparedness and response strategies.

3 Novel methods for detecting empirical evidence

MYRIAD-EU uses a range of novel approaches to detect changes in reported losses and damages due to spatial and temporal dynamics in hazard, exposure and vulnerability caused by: (1) interactions between multiple hazards; and (2) DRR measures taken to address those hazards. We recognise that a plethora of databases and functions exist. This section does not aim to provide a comprehensive overview of all existing databases and functions, but instead focuses on those that have been identified for use in MYRIAD-EU. Therefore, this section first discusses existing key databases and vulnerability functions that have been identified for use in MYRIAD-EU to address dynamics and feedbacks of risk. Next, we discuss a novel vulnerability drivers database for six different hazards that was developed by MYRIAD-EU. Then we discuss several statistical and machine learning techniques that have been identified to detect different aspects of disaster risk dynamics. Finally, we outline how Disaster Forensic Analysis are used to study past events and learn lessons regarding disaster dynamics and the impact of DRR measures.

3.1 Examination of existing databases and functions

We use existing disaster loss databases and statistics that exist at global, EU, and national scales (e.g., NatCatService, CATDAT, EM-DAT, EUROSTAT, Post Disaster Needs Assessments, national accounting) to identify losses and damages, several existing DRR/adaptation databases (e.g., RISC-KIT, ClimateADAPT, FLOPROS). This allows us to specifically examine changes in exposure and vulnerability across different groups (e.g., elderly, female) while accounting for a multi-hazard risk context. Table 1 presents many existing damage and loss databases that are of relevance for MYRIAD-EU.

Table 1: A summary table of existing European damage and loss databases for natural perils. In many cases, the database has a global, or at least European, extent with a differing range of hazards included.

Name	Author	Extent	Hazards Covered	Years	Socio-economic metrics covered	Level of coverage	Open?	Multi-hazard?
EM-DAT	UC Louvain, OFDA, CRED	Global	All natural and manmade	1900-2023	Fatalities, Social effects, Econ. Damage	26000+ events	Yes, restricted public use with sign in; Not freely downloadable	No
GDIS	CIESIN, Rosvold and Buhuag (2021)	Global	All natural and manmade	1960-2018	Fatalities, Social effects, Econ. Damage	11081 events	Open	No
CE-DAT	CRED	Global	Complex emergencies	1998-present	Fatalities, Social effects, Econ. Damage	4000+ events	Yes, restricted public use with sign in; Not freely downloadable	No
JRC DRMKC	JRC	Europe	All natural and manmade	Historical-2023	Fatalities, Social effects, Econ. Damage	1000+ events	Yes	No
EEA-CATDAT	Risklayer/CMCC	Europe	All natural	1980-2023	Fatalities, Economic Metrics	5000+ events	Statistics open, database not freely downloadable	No
Brakenridge et al.	Dartmouth / Uni Colorado	Global	Hydrological	1985-2023	Fatalities, Social effects, Less on Econ. Damage	5000+ events	Yes	No
AON ImpactForecasting	AON	Global	All natural and manmade	2001-2023	Mostly Econ. Damage, Claims and fatalities	ca. 2500 events	Open publications, but restricted use of results.	No
NatCatService and MRNATHAN	MunichRe	Global	All natural	79-2023 (Mainly 1980-2023)	Mostly Econ. Damage, Claims and fatalities	Over 40,000 loss events	Statistics open, database not free to download; MRNATHAN on original CD	No
Sigma	SwissRe	Global	All natural	1970-present	Mostly Econ. Damage, Claims and fatalities	1000s of events	Statistics open, database not freely downloadable	No
GLIDE	Asian Disaster Reduction Center (ADRC)	Global	All natural and manmade	2000-present	Fatalities, Social effects, Econ. Damage	1000s of events	Yes	No

Desinventar	Country-Specific Govts	90+ countries	All natural and manmade	Country specific generally recent	Extensive social, economic and environmental damage parameters	100,000s of events and datacards	Yes	No
NOAA Earthquake, Volcano and Tsunami	NOAA	Global	Earthquake, Volcano and Tsunami	Historical-present	Fatalities, Social effects, Econ. Damage	Earthquake: 6384 events	Yes	No
GLC	NASA	Global	Landslide	1970-2021	Fatalities, Social Effects	11033 events etc.	Yes	No
GVP	Smithsonian Institution	Global	Volcanic activity	Historical-present	Descriptions of social effects	Covers 1500+ volcanoes	Yes	No
GFDRR DL-DAT	World Bank	Selected	All natural	1974-present	All social and economic sectors	Around 150 events	Yes	No
CATDAT	Daniell et al. (2014)	Global	All natural and manmade	Prehistoric-present but mainly 1900-present	Fatalities, Social effects, Econ. Effects, Economic sectors	Over 60,000 loss events	Statistics open, database not freely downloadable	No
Volcano Fatalities Database	Brown et al. (2017)	Global	Volcano	1500-2017	Fatalities	635 records	Freely downloadable CC0	No
Landslide Fatality Database	Froude & Petley (2019)	Global	Landslide	2004-2017	Fatalities, Extent, Effects	5490 events	Freely downloadable CC0	No
BD NATDIS Global	Ubyrisk Consultants	Global	All natural and manmade	2001-2023	Fatalities, Economic damage	20,702 events	Statistics open, database not freely downloadable	No
GIDD	IDMC	Global	All natural and manmade	1998-present	Displacement	By country, but events also available	CC-BY-NC	No
EUFF	Petrucci et al. (2021)	Europe	Hydrological	1980-2020	Fatalities	2875 events	Freely downloadable CC0	No
GAPHAZ	Uni. Oslo	Global	Glacier and Permafrost Hazards	Historical-present	Disaster impacts	87 events	Freely downloadable CC0	No
Cambridge Earthquake Database in combination with Pomonis database	Uni.Cambridge	Global	Earthquake	1900-2023	Fatalities, Economic damage, Building damage	1800+ events	Statistics open, database partially freely downloadable	No

RSOE EDIS	RSOE	Global	All natural and manmade	2004-2023	Fatalities, Building damage and social effects where available	1000s of events	Statistics open, database not freely downloadable	No
GallagherRe & WillisRe	GallagherRe & WillisRe Under diff publications	Global	All natural and manmade	2012-2023	Fatalities, Economic metrics (total, insured)	ca. 200 events per year	Via Publication – not for public use	No
EFFIS	JRC	Europe	Forest fire hazards	2000-2023	Forest fire extents, social effects where available	1000s of events	Yes	No
HANZE	Paprotny et al. (2017)	Europe	Hydrological	1870-2016	Fatalities, Economic damage, Building damage	1564 events	Open, downloadable. Includes compound floods	No
WMO	WMO based on EM-DAT	Global	Hydrological and Meteorological	1970-2019	Fatalities, Economic damage, Building damage	11778 events	Statistics open, database not directly freely downloadable	No
ESWD-ESSL	ESSL	Europe	Weather related	Historical-2023	Fatalities, Building Impacts	33000+ events	Yes, after registration, limited use.	No
PAGER-CAT	Allen et al. (2008)	Global	Earthquake	1900-2007	Fatalities, Economic damage, Building damage	2000+ events	Yes	No
FAOSTAT	FAO (2021)	Global	All natural and manmade	1970-2019 with focus on 2008-2018	Economic impacts on agriculture	1000s of events	In publication form	No
EDII and EDR	European Drought Centre and R&SPI project	Europe	Drought	1900-2021	Sectoral impacts, economic damage etc.	500 drought impact reports as of 2021 with 30 or so events	Yes	No

3.1.1 Existing disaster loss databases and statistics

We have identified well-established data sets in the field of natural hazards that are open access for academic use. Below we outline key databases that we (plan to) use in WP4 to assess dynamics and feedbacks of risk, and discuss their advantages and limitations:

EM-DAT Emergency Event Database

- Description:
  EM-DAT contains global data on the occurrence and impacts of mass disasters from 1900 – present. Events may be included if they resulted in at least 10 deaths, at least 100 people affected/injured/homeless or the affected country issued a declaration of emergency or an appeal for international assistance. Data are obtained from various sources, including United Nations (UN) agencies, research institutes and non-governmental organisations. EM-DAT records data on different types of natural hazards including floods (fl), droughts (dr), earthquakes (eq), volcanic activity (vo), extreme wind (ew), heatwaves (hw), cold waves (cw), wildfires (wf), landslides (ls) which are central to MYRIAD-EU's Pilots. The EM-DAT database states the primary hazards as well as secondary, associated or resulting hazards (up to two), thus including a certain type of multi-hazard event. It includes so-called compound events, which were classified as preconditioned, multivariate, temporally compounding or spatially compounding events by Zscheischler et al. (2020), which are similar to the so-called triggered or spatially and temporally coinciding hazards as identified by Gill & Malamud (2014). Nonetheless, most events are recorded as single-hazards (Figure 1).

- Limitations:
  - The EM-DAT database does not include consecutive disasters at the same location, if they were not triggered. This is a limitation for multi-hazard analysis, because consecutive disasters can lead to significant compounding impacts and need to be accounted for when developing robust DRR measures (e.g., de Ruiter et al. 2020, de Ruiter & Van Loon, 2022).
  - Other limitations of the database for the purpose of multi-risk analysis, in particular of dynamics and feedbacks of risk drivers, are related to data availability and resolution/accuracy:
    - Data on hazard magnitude are scarce. Only the magnitude of the main hazard but not of the associated hazards is included. Moreover, for more than half of events, and also recent events after 2000, this information is missing, and quality or accuracy are questionable.
    - Data on location are mostly given in terms of administrative boundaries, thus not providing an accurate representation of spatial extent of the event. This is combined with GDIS for some cases to give an approximate extent, however it is not consistent.
    - The variable Total people Affected is not interpreted consistently across events and can hardly be used for comparison.
    - Economic damage is reported from different entities and uses different and conflicting definitions.
    - The inflation adjustment does not use Country CPI and thus assumes all countries are the United States.

- Exploratory data analysis:
  An exploratory data analysis was conducted where we focused the analysis on event types that have been recorded at least 10 times and cause impacts at larger than local spatial scales. For example, landslides have been excluded due to their mainly local impact. These remaining hazards include extreme wind, cold waves, heatwaves, droughts, floods, earthquakes, and any combination. Because earthquakes have not been recorded in combination with other hazards these are also excluded. The following multi-hazard events remain: extreme wind and floods, extreme wind and cold waves, heatwaves, and droughts. This is according to the EM-DAT definition of single- and multi-hazards, meaning that they do not have any associated hazards registered. A challenge when analysing impact, and ultimate changes in impact, is that many events miss data on impacts. Table 2 shows the total number of events recorded per type, as well as the number that have recorded "Total Deaths", "Total Affected" and "Total Damages, Adjusted ('000 US$')". Impact data are especially scarce for drought, heatwaves, and drought-heatwave combinations with fewer than 10 data points. Impact data are also limited for cold waves, extreme wind events, and combinations (< 20 data points). Considering the data quality (see limitations of EM-DAT above), we focused on a comparison of losses and damages to floods, extreme wind events and combinations, as those have more data available (> 150 data points). Figure 2 shows boxplots of impact distributions for floods, extreme winds and flood – extreme wind multi-hazards in terms of "Total Deaths", "Total Affected" and "Total Damages, Adjusted ('000US$')". By visual inspection, the impact on people in terms of "Total Affected" as well as economic losses in terms of "Total Damages, Adjusted ('000US$')" tends to be notably higher for multi-events consisting of floods and extreme winds than for single-hazard events, either floods or extreme wind. This is not visible for "Total Deaths" in the case of flood versus combined flood – extreme wind events. On the other hand, the impacts of combined events do not seem to be an addition of the impact of the single-hazard events supporting the theory that there are dynamics between risk drivers leading to non-linear relationships. However, these are very preliminary conclusions given the quality of the data set as described above. The data set gives very little opportunity for robust statistical analysis.

- <u>Next steps:</u>
  To make the data set suitable for an in-depth statistical analysis of changes in losses and damages that arise from interactions between multiple hazards in MYRIAD-EU we plan to:
  - make use of additional data sources (this will be addressed as part of Task 4.4):
    - for currently missing impact data
    - for currently missing data on hazard intensities
  - investigate a wider definition of multi-hazard events, for example, consecutive events such as the tropical cyclone and earthquake in Haiti in 2019 and the two tropical cyclones making landfall in Mozambique in 2020 (see, e.g., de Ruiter & van Loon 2022) (this will be addressed as part of Task 4.4).

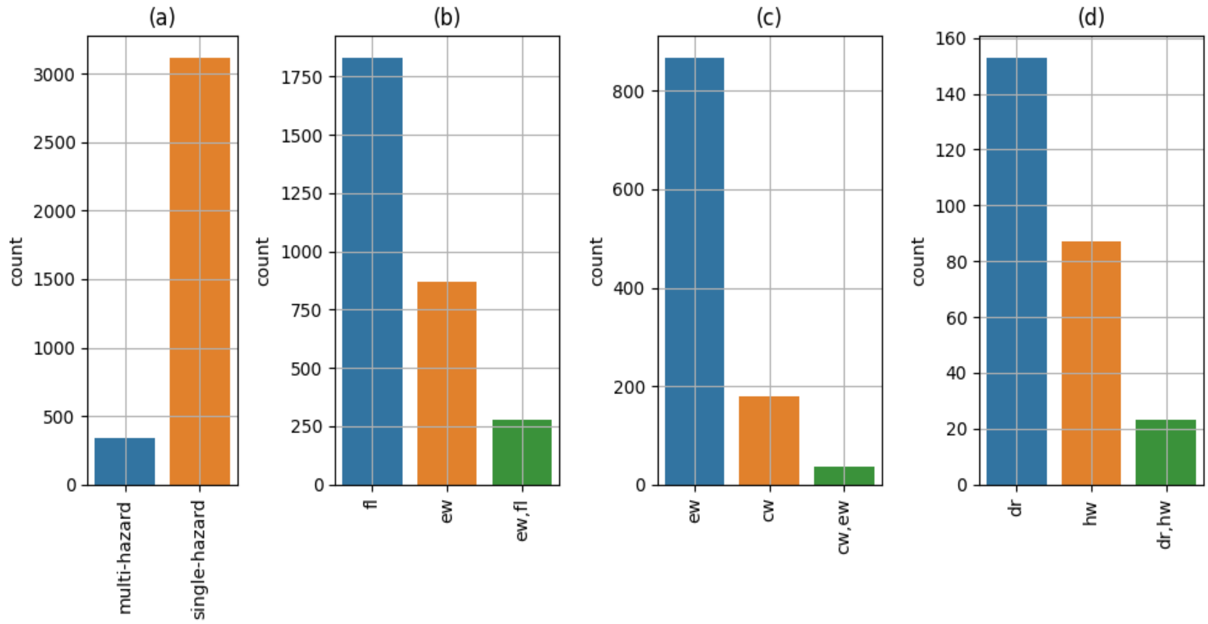

Figure 1: Total number of disaster events as registered in EM-DAT from 2000 to 2015, with fl = flood, ew = extreme wind, cw = cold wave, dr = drought, and hw = heatwave. Only events with a total number of at least 10 and with hazard types that have been recorded as single- and multi-hazards events are included in the plot. (a) Total number of multi- and single-hazard events, (b) for events with fl and ew hazards (c) events with ew and cw hazards, (d) events with dr and hw hazards.

Table 2: Total number of events compared to total number and fraction of events that have impact data, with fl = flood, ew = extreme wind, cw = cold wave, dr = drought, and hw = heatwave.

Event Type	Total number of events	Number of events with registered "Total Deaths"	Number of events of events with registered "Total Affected"	Number of events of events with registered "Total Damages, Adjusted ('000 US$')"
fl	1832	1227	1594	483
ew	868	600	576	401
cw	179	148	55	14
dr	153	5	96	54
hw	87	80	31	5
ew,fl	277	217	232	152
cw,ew	36	26	13	17
dr,hw	23	12	5	18

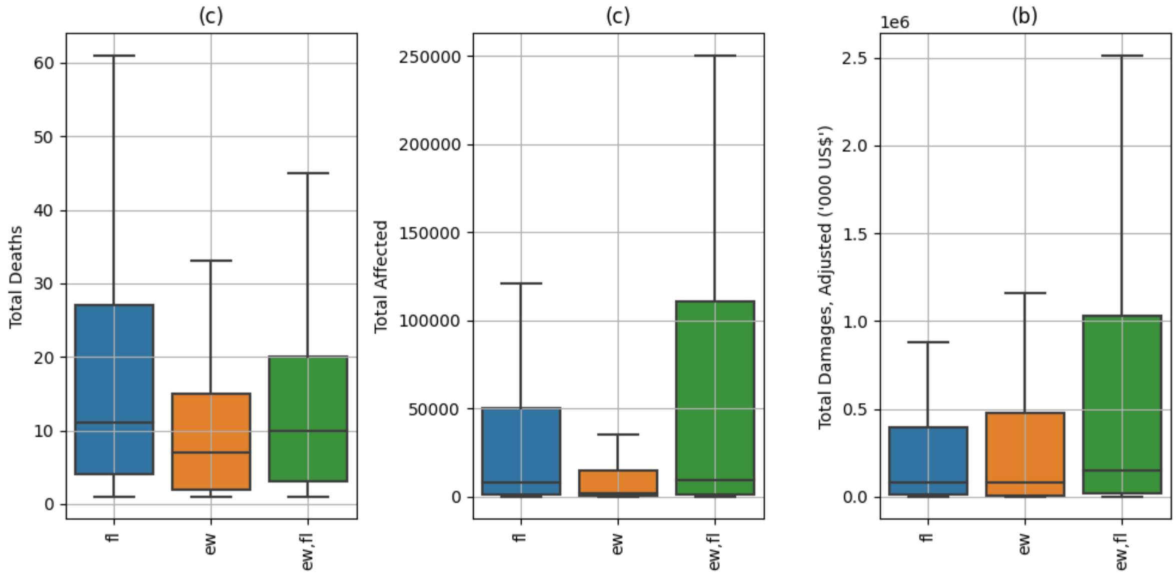

Figure 2: Impacts for floods, extreme winds and flood – extreme wind multi-hazards in terms of (a) "Total Deaths", (b) "Total Affected" and (c) "Total Damages, Adjusted ('000US$')", with fl = flood, ew = extreme wind, cw = cold wave, dr = drought, and hw = heatwave.

ESWD (European Severe Weather Dataset)

- Description:
  The ESWD is managed by the European Severe Storms Laboratory (ESSL) with the support of other public and private organisations and individuals (CMCC became a full institutional member in 2022). The objective of the ESWD is to collect and provide detailed and quality-controlled information on severe convective storm events over Europe. The events are geo-referenced and time-referenced and divided per category of hazard, providing in some cases information on the intensity of the event (such as wind speed or dimension of hail) and its impacts on population, infrastructures, buildings and more. The reporting criteria state that ESWD is intended to be a database that only contains important weather events that can endanger people or do damage. Reports can be submitted by all individuals (they may come from local

newspapers, social media, scientific reports, etc.), but different quality checks are carried out by ESSL (or their partners) to verify them. The first level, (QC0+) checks the plausibility of the report, mainly confronting the type of events with the general meteorological conditions of that day and area); the second (QC1) means that the report was confirmed by a reliable source; the third one (QC2) means all the pieces of the reports have been validated thoroughly (typically assigned to reports based on cases studies on a scientific level).

- Limitations:
  - Not all hazard types are included in this dataset, but only those related to convective storms (extreme wind, extreme rain, in particular).
  - The objective of the dataset is to provide a catalogue of extreme events: impact descriptions are not always available and may not be very detailed.
  - The consistency of the reports during the years may vary, due to the increasing size of the network of associated partners, reporting individual and general attention to extreme weather events. For example, Figure 4 shows that the number of hail reports has greatly increased in the last few years in the Veneto Region, but it is due mainly to better recording practices than shifts in hail trends. If statistical or machine learning methods are to be trained on such data, it is of paramount importance to select time frames in which the reporting rate is (mostly) consistent.
- Exploratory data analysis:
  Data from ESWD has been explored within the Veneto pilot, mainly for hazards related to extreme wind and extreme precipitation. Figure 3 shows a summary of the main events recorded in the Veneto area in a selected timeframe (2009-2022). The total number of events is close to 2000 and most of them (95%) are in the second quality control category (i.e., confirmed by reliable source) and provide a general description of the impacts.

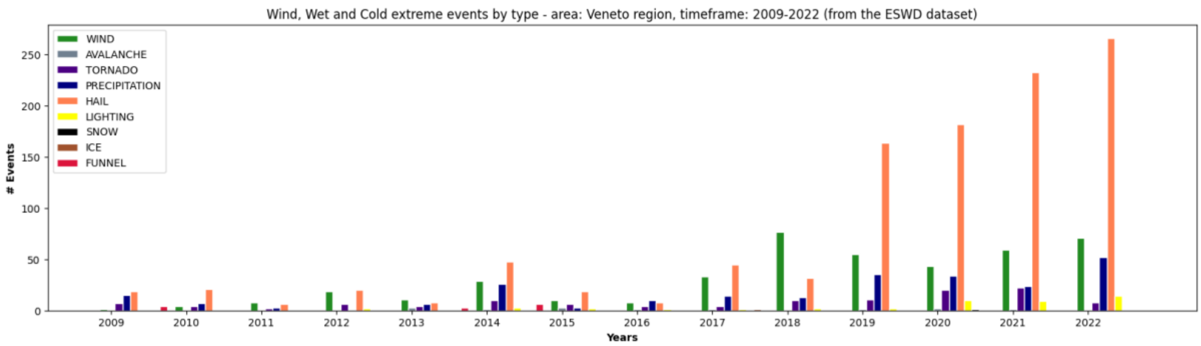

Figure 3: Wind, wet, and cold extremes in the Veneto region (2009-2022).

Other impact and loss databases at a National Level

Impact and loss databases at a national level will be discussed within D5.2 and have been discussed for the pilots in D3.3.

3.1.2 Existing vulnerability functions that address dynamics

Several European research projects have already contributed to the body of knowledge on vulnerability, and MYRIAD-EU aims to include and build on their advances. Some notable examples (as presented in the Milestone 18 document) are:

- RISK-UE (An advanced approach to earthquake risk scenarios with applications to different European towns) focused on an advanced approach to earthquake risk scenarios and the researchers created a set of dynamic vulnerability curves for different types of buildings across Europe based on empirical data and expert judgement (Lagomarsino & Giovinazzi, 2006). More recent advances have started to incorporate temporal changes in vulnerability into these models. Silva et al. (2014) developed a temporal vulnerability assessment methodology that takes into account variations in the vulnerability of buildings due to factors like structural ageing, modifications, and maintenance. By modelling these changes over time, they were able to provide a more nuanced perspective on vulnerability, demonstrating how seismic risk can increase or decrease based on these factors.

- SYNER-G (Systemic Seismic Vulnerability and Risk Analysis for Buildings, Lifeline Networks and Infrastructures Safety Gain) is a prime example of dynamic vulnerability assessment in Europe. The project aimed to provide an advanced methodological framework for systemic vulnerability and risk analysis (Pitilakis et al., 2014). It developed a comprehensive methodology to quantify the seismic vulnerability of structures and infrastructure networks, considering the cascading effects within the physical and socio-economic environments. The project developed fragility functions for buildings, considering factors such as age, building type, and material, which dynamically change over time. Moreover, SYNER-G expanded its analysis to consider interdependencies between different elements of a city's infrastructure system (Selva et al., 2017). For instance, it identified how damage to the power supply network can influence the functionality of the transportation and healthcare systems. This systemic perspective recognises the dynamic nature of vulnerability and its influence on the overall resilience of the urban environment.
- MATRIX (New Multi-Hazard and Multi-Risk Assessment Methods for Europe): was another significant project that focused on assessing multi-hazard risks across Europe (Zschau et al., 2016). MATRIX developed new methods and tools for multi-hazard and multi-risk assessment, considering different types of hazards (e.g., earthquakes, floods, landslides) and their interrelations. This comprehensive approach to risk assessment provides a more holistic understanding of vulnerability and improves the effectiveness of mitigation strategies. Specifically, MATRIX developed an Integrated Risk Assessment Module, which considers the potential interactions between different hazards and vulnerabilities in a system. This reflects the dynamic nature of vulnerability and provides a more realistic assessment of risk under different disaster scenarios.
- STREST (Harmonised approach to stress tests for critical infrastructures against natural hazards) has made considerable contributions to vulnerability functions for infrastructure that encompass the interaction between various components of infrastructure networks, highlighting their interdependencies, identifying seven critical infrastructure sites in Europe and developing stress test methodologies to evaluate their vulnerabilities (Mignan et al., 2016). STREST also emphasised the importance of a systemic risk assessment approach that considers not only physical damage but also functional disruption and interdependency effects. In addition, Pregnolato et al. (2017) developed a dynamic vulnerability model for flood risk to bridge networks in the UK, considering the temporal variation in water depth and flow velocity during flooding events. The model used time-dependent fragility curves, which allowed for an accurate estimation of the failure probability at different times during the flood.
- 21mbrace (Building resilience amongst communities in Europe) built an integrated framework to measure community resilience to natural hazards in Europe, using a set of indicators that capture both the exposure and adaptive capacity of communities (21mbrace, 2015) thus accounting for the adaptive capacity of a community or system,

as it affects how a system responds and recovers from damage, in dynamic vulnerability functions.

In addition, there are recently funded projects such as MEDiate (The project – Mediate Project (mediate-project.eu)) or the software VIGIRISKS from BRGM (https://www.brgm.fr/en/reference-completed-project/vigirisks-all-one-predictive-platform-natural-risks) who are also working on dynamic vulnerability functions.

3.1.3 Existing hazard, exposure and vulnerability databases

Below we discuss key existing hazard, exposure, and vulnerability databases that have been identified for use in MYRIAD-EU.

Global Human Settlement Layer

- Description:
  The Global Human Settlement Layer (GHSL) consists of several data products on global population and built-up distributions. It uses satellite imagery, census data, and volunteered spatial information to create information on the human presence on Earth over time. The satellite imagery provides information on the Earth's build-up area in a gridded format. Census data are used in combination with the satellite imagery to assign population to specific regions, cities, towns, etc. on Earth. Finally, by applying a certain threshold on the amount of population or built-up area in each grid cell, distinctions between urban and rural regions are made (GHSL Data Package 2023, 2023). The resolution of the data varies between 10m to 30arcseconds, depending on the product. Note that all products have at least a 1km resolution option. In general, this dataset provides a useful globally- consistent coverage of data on exposure. Furthermore, this dataset is especially useful when assessing risk in urban regions because it provides a consistent and physical definition of cities, as opposed to spatially strongly differing administrative definitions of cities (UN-DESA, 2019).

- Limitations:
  - First of all, satellite imagery requires extensive pre-processing before it can provide any information, and this can introduce inaccuracies.
  - Census data may not always be up-to-date or may even be missing at all for some regions (Kuffer et al., 2022).
  - A part of the population may also be left out of the census data (e.g. those living in informal settlements; Kuffer et al., 2022).

- Exploratory data analysis:
  The Global Human Settlement Layer Degree of Urbanisation (GHS-SMOD) data layer is used as a measure of exposure, to focus the multi-hazard recovery analysis on areas with human presence as described in section 3.2.2.

Veneto Region Emergency Dataset

- Description:
  This dataset focuses on impacts in the coastal municipalities of the Veneto region: impacts were extracted from the Decreto del Presidente della Giunta Regionale reports (DPGR, namely Decree of the President of the Regional Council) which collects the activation of the regional state of crisis, namely 'Stato di Crisi'. For each impact, these documents provide qualitative information on the reported damages, the list of the municipalities affected and the dates when the impact took place. Typologies of the damages reported include physical damages related to urban flooding,

agriculture/fisheries, people (e.g., fatalities, injuries, displacements), beaches (e.g., shoreline erosion, debris accumulation), structures/infrastructures, economic activities, and tertiary sector.

- Limitations:
  - Reports may be incomplete and misleading: not all impacts that created an economic loss or a service interruption have been recorded, but only those that triggered an emergency request from the region. Thus, only events causing massive or extensive damages have been recorded; moreover, impacts from hazards such as heatwaves are not present in this dataset.
  - Moreover, each report lists the affected municipalities and the overall period but does not provide information on which date each municipality was affected.
  - Similarly, the typology of damage, when present, is not associated with a specific date or municipality. Ideally, more detailed data and reports would be required to accurately assess the quantitative extent of the impacts, including information such as coordinates, specific damage types, and monetary costs of restoration. However, such detailed quantitative data on impacts and their economic costs are not publicly available. Therefore, the impact dataset consists of pairs representing the day and municipality where an impact occurred.

- Exploratory data analysis:
  To improve the accuracy of the input dataset, each impact was cross-checked with local newspapers (within activities in the frame of AdriaClim project: https://www.cmcc.it/projects/adriaclim-climate-change-information-monitoring-and-management-tools-for-adaptation-strategies-in-adriatic-coastal-areas). This verification process aimed to identify additional events that caused significant damages to the population or infrastructure but were not reported in the "Stato di Crisi" database. Consequently, the final impact dataset comprises a total of 447 days of impacts from extreme weather events across eleven Veneto coastal municipalities during the period from 2009 to 2019.

Environmental quality datasets from monitoring stations

- Description:
  Losses and impacts on environmental quality were explored within the Veneto pilot activities with regards to water quality, air quality and vegetation. In particular, data from monitoring stations installed by ARPAV (regional agency for environmental protection and prevention in Veneto) on Veneto rivers (in particular for Adige and Brenta) and near urban centres for air quality. Information on vegetation status can be recovered through satellite images, analysing indicators such as NDVI (Normalised Diffraction Vegetation Index), LAI (Leaf Area Index), VCI (Vegetation Condition Index), and VHI (Vegetation Health Index). These indicators may be retrieved from Copernicus Land service (https://land.copernicus.eu/global/products/ndvi) or from MODIS (https://modis.gsfc.nasa.gov/data/dataprod/mod13.php).

- Limitations:
  These impact datasets typically have a coarse temporal resolution, with few snapshots of data available per year. This may pose problems when trying to model dynamic risk factors caused by extreme weather events, because the variability of impact data may be limited. For example, measurements of river water quality may have been taken days or weeks after an extreme event, so its impact may not be recorded at all.

- Exploratory data analysis:
  Several parameters are measured that can provide information on the chemical, physical characteristics of the water, nutrients, and microbiological organisms. In particular, temperature, pH, dissolved oxygen, suspended solids, phosphates, and nitrates are recorded from 2010 to 2022 on a monthly basis (which can vary from station to station). This dataset can be used to analyse the impact caused by multi-hazard events, changes in land-use and anthropic activities on river water quality. With regards to air quality, data on PM2.5, PM10, and Ozone can be leveraged to study the changes and feedback dynamics between extreme weather conditions, air quality and impacts on socio-economic and environmental systems. Vegetation data are available from 2000 to present day, at high spatial resolution (up to 250m), with a temporal resolution that can vary from few days (10 days) to several months (3 months for some LAI layers).

Other datasets

These datasets provide a preliminary insight into exposure and vulnerability databases, however there are many others for use in Europe within the project which will be described in WP5 such as WSF 3D from DLR (Esch et al., 2022), CATDAT (Daniell et al., 2014), HANZE (Paprotny & Mengel, 2023), other GHSL products (JRC, 2023; Melchiorri & Kemper, 2023), GPW (CIESIN, 2023), EUROSTAT (Corbane & Sabo, 2019; Batista e Silva et al., 2013), Facebook HRSL, LitPop (Eberenz et al., 2020), WorldPop, HILDA (Fuchs et al., 2013), HYDE (Klein Goldewijk et al., 2017), Kummu et al. 2018; EEA – CLC (2023), as well as building level databases such as OSM, Google and Microsoft and other cadastral datasets.

3.2 Novel vulnerability drivers database

Not everyone is equally affected by natural hazards; some people or assets are more vulnerable to the adverse effects of hazards than others. Although we know to some extent what drives vulnerability, it remains challenging to operationalise “the vulnerable” (Raška et al., 2020; Hinkel, 2011) and to unravel the interactions between different vulnerability drivers (Ayanlade et al., 2023; Simpson et al., 2023; de Ruiter & van Loon, 2022). Furthermore, recent research shows that 85% of the social vulnerability theories are not explicitly explained in the literature (Kuhlicke et al., 2023). in a multi-hazard context, acknowledging the significance of social vulnerability takes centre stage. While comprehending the physical aspects of hazards remains crucial, equal emphasis must be placed on understanding the social, economic, and cultural factors that shape a community’s resilience (Bergstrand et al., 2015; Ryan et al., 2020). Social vulnerability encompasses the predisposition of certain individuals or groups to endure disproportionate impacts and hardships during hazardous events (Winsemius et al., 2018). Factors such as poverty, inequality, inadequate infrastructure, limited resource access, and marginalised social groups exacerbate vulnerability (Drakes & Tate, 2022). By delving into research on social vulnerability within the context of multi-hazards, we can uncover and address systemic issues underlying differential impacts and develop targeted interventions to bolster community resilience (Fatemi et al., 2017; Fraser, 2021). Understanding the social dynamics and inequalities associated with multi-hazard events empowers policymakers and stakeholders to implement equitable strategies, prioritise the needs of vulnerable populations, foster inclusive decision-making, and ensure that no one is left behind in the face of disasters (Bergstrand et al., 2015; de Ruiter & van Loon, 2022).

To address this gap, MYRIAD-EU has created VulneraCity, a database of urban vulnerability drivers, to find out what drives the vulnerability in cities to several different hazards (pluvial flooding, coastal flooding, drought, heatwaves, earthquakes, and waterborne diseases; Stolte et al., submitted for publication). We look at cities specifically because of the high amount of concentration of exposed people and assets (UNDRR, 2019; UN, 2019). We apply a systematic literature review – not a novel method on its own, but to our knowledge never used before to find the drivers of vulnerability to multiple hazards in such an extensive manner. In total, we have reviewed over 3000 studies, from which we gathered close to 1500 unique vulnerability drivers out of around 500 studies. Our focus has been on empirically derived drivers of vulnerability, but we also include drivers that are acquired by models, theory, adoption, or unknown methods.

Each driver in VulneraCity is classified based on vulnerability dimension (social or physical), sub dimension (e.g. economic, demographic, critical infrastructure), class (e.g. drainage, poverty, preparedness) and acquisition method (e.g. empirical or modelled). The database can be used to find out what drivers are important across different hazards and help us further in determining which drivers may be relevant to multi-hazards. Our results show for instance that drivers related to conveying and gathering hazard information and warnings are among the most important for all investigated hazards, whereas the importance of drivers linked to water supply is more restricted to just drought and waterborne diseases. (Figure 4; Stolte et al., submitted for publication).

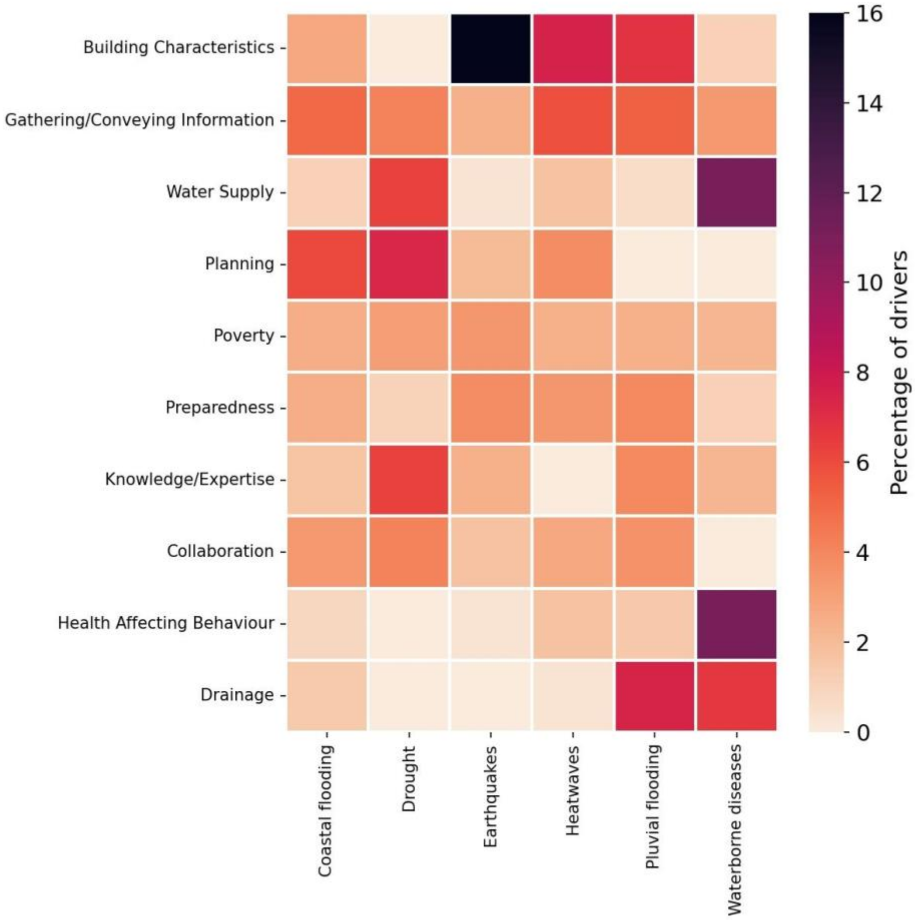

Figure 4: Heatmap showing the percentage of vulnerability drivers in each class (rows) per hazard (columns), relative to the total number of vulnerability drivers for that hazard. This Figure only shows the 10 most common classes, which are determined by ranking the classes on the sum of the rows.

VulneraCity can also be used to find similarities and differences in the vulnerability profiles of the different hazards. Here, we present two examples: that of drought (Figure 5) and earthquakes (Figure 6). The Sankey diagrams in Figures 5 and 6 show the importance of each sub-dimension and class of vulnerability for the two hazards. Thicker lines mean that more drivers fall into that sub-dimension/class, indicating a larger importance. Both hazards show significantly different vulnerability profiles. For instance, governance-related vulnerability appears to be more important for drought than for earthquakes, whereas vulnerability of general urban assets (i.e. those assets in the city that do not belong to the critical infrastructure or the living environment) are very prominent in earthquakes, but almost non-existent for drought. In this case, we can explain these differences by the nature of the hazards. General urban assets, like residential buildings, are important for earthquakes because of the physical damage resulting from an earthquake. However, such assets are hardly affected by droughts. Governance is arguably important for each hazard, but it is extra salient for drought as the effect of the hazard can be strongly mitigated by ensuring proper water supply and demand management. A more extensive elaboration on the commonalities and differences of the investigated hazards' vulnerability drivers can be found in Stolte et al. (submitted for publication).

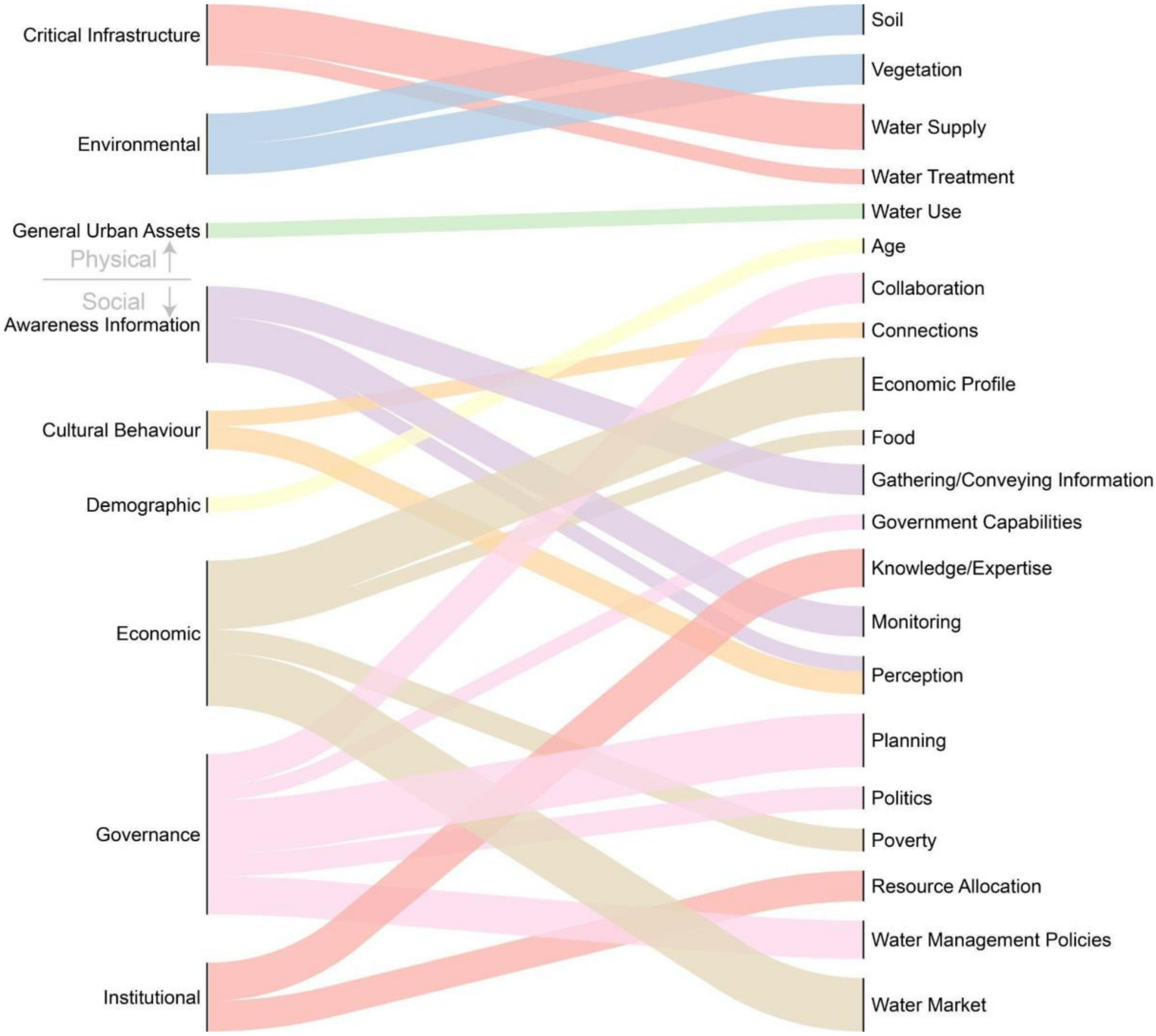

Figure 5: Sankey Diagram showing the relationship of sub-dimensions and classes for drought. Each line represents a number of drivers that flow from a sub-dimension into a class. For readability, we only display those sub-dimension-class combinations that contain at least 2 drivers.

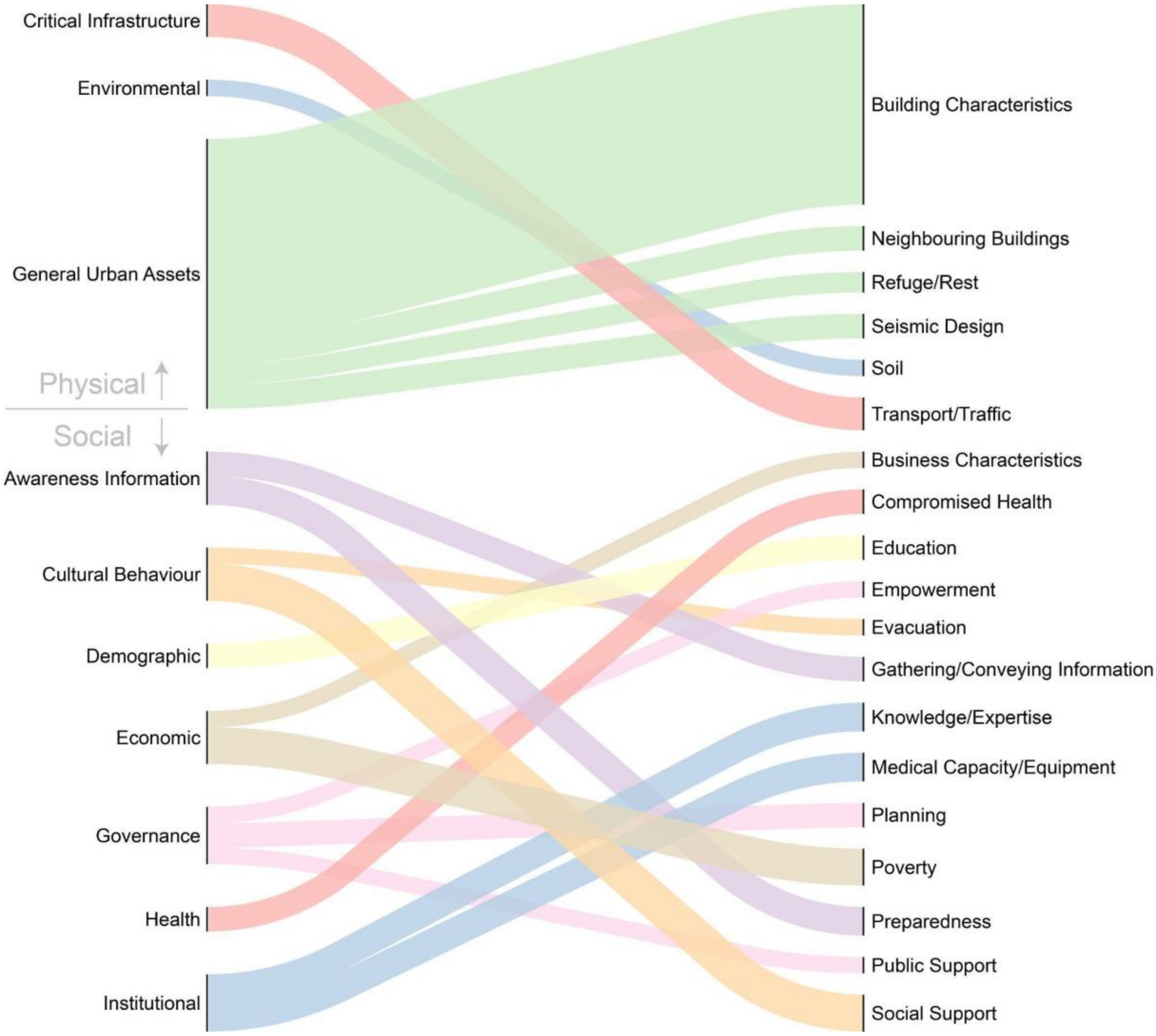

Figure 6: Sankey Diagram showing the relationship of sub-dimensions and classes for earthquakes. Each line represents a number of drivers that flow from a sub-dimension into a class. For readability, we only display those sub-dimension-class combinations that contain at least 4 drivers.

Finally, one could also bring the list of drivers in VulneraCity to urban policy makers, authorities, or other stakeholders to work out which drivers of vulnerability are relevant to their city and to consequently act on those vulnerabilities. Altogether, this database gives us the opportunity to discuss vulnerability in a more holistic way than before.

VulneraCity shows a wealth of potentially relevant drivers, but does not tell us what data are available to assess these drivers. Therefore, we also want to review existing urban datasets at a supranational (i.e., including cities from multiple countries) level. We opt for the supranational level because it is valuable to know how cities compare to each other to find out which places need the most urgent assistance in reducing their vulnerability. Together with VulneraCity , we can now find out which data are important yet missing to do a large-scale vulnerability assessment. Furthermore, we can potentially use the data as input for Machine Learning techniques with which we can fill in data gaps for specific cities.

We can also use both VulneraCity as well as our review of urban vulnerability data to further our understanding of vulnerability dynamics. There are different aspects of vulnerability dynamics that we can address: (1) Dynamics over time can be addressed if we find longitudinal data for cities in our review. (2) Schipper (2020) discusses the dynamics in vulnerability during adaptation. We also found several examples of this type of dynamic. For instance, mobile phones make it in theory easier to issue warnings and to communicate during a flood event. However, there have been several events in the past in which mobile phone signals were jammed because of flooding. It can thus lead to a false sense of security (Chandra & Gaganis, 2016). Mobile phones as a way to convey information during flooding is therefore an example of a vulnerability rebound effect (Schipper, 2020) in which the intention was to reduce vulnerability, whereas in reality vulnerability has increased. (3) We found several examples of directional vulnerability in our database. This relates to the way in which a change in a vulnerability driver translates into a change in the impact of a natural hazard. In most research, a one-directional relationship is assumed, but we found five additional forms of this relationship (see Figure 7 for schematic drawings of this):

- One-directional vulnerability: A driver that always results in either an increase or decrease of a city/citizen's vulnerability to all hazards. Example: Disaster preparedness is generally considered as something that makes cities and citizens less vulnerable to all hazards, among others by: performing drills and thus becoming more skilled in dealing with disasters (Karavokiros et al., 2016; Chou & Wu, 2014; Braun & Assheuer, 2011; Goudet et al., 2011), storing emergency materials/supplies to increase survivability during disasters (Kundak, 2017; Chandra & Gaganis, 2016; Martens et al., 2009), and disaster training for medical personnel or city officials to improve reaction and recovery times (Daly et al., 2017; Knowlton et al., 2014).
- Bi-directional vulnerability: A driver that can lead to both an increase and a decrease in vulnerability at the same time, or that simultaneously makes a city/citizen more and less vulnerable to a hazard. Example: A retired elderly person does not need to do heavy labor during a heatwave (less vulnerable than other citizens; Bradford et al., 2015), but may have a weaker physique (more vulnerable than other citizens; Huang et al., 2022; Bradford et al., 2015; Bambrick et al., 2011).
- Asynergies: A driver that decreases vulnerability to one hazard but simultaneously increases the vulnerability to another hazard. Example: Urban drainage systems are important in times of pluvial flooding (Tellman et al., 2018 Vianna Mansur et al., 2018), but can also distribute the water more easily into the city during a coastal flood event (Shen et al., 2019). Furthermore, if the drainage system gets rid of the water too fast, it impedes evaporative heat loss whilst this type of cooling can be beneficial in times of heatwaves (Kislov et al., 2020).
- Compounding vulnerability: Two vulnerability drivers that together have an amplifying effect on the total vulnerability, making the combined outcome worse than the sum of their individual parts. Example: Elderly migrants with neuro-cognitive conditions (e.g. dementia). Elderly people experience an increased vulnerability to several hazards because age frequently comes with reduced physique (Schuster et al., 2017), impeding mobility during a disaster (Taylor et al., 2022). This can be compounded by the fact that migrants may experience a language barrier in information dissemination (Hansen et al., 2014; Martens et al., 2009), especially when they have a neuro-cognitive condition that may reduce their ability to understand a non-native language (Hansen et al., 2014).
- Conditional vulnerability: Drivers that change the vulnerability under certain conditions only. Example: In a patriarchal society, women in informal settlements are generally responsible for household tasks that bind them to home and which makes them more vulnerable to pluvial flooding than men (Kayaga et al., 2021; Schofield & Gubbels, 2019; Chandra & Gaganis, 2016). But a woman in a more affluent community – in that same patriarchal society – may have resources to let servants do the heavy repairments on

her home after flooding, making her less vulnerable compared to men–(Grasham et al., 2019; Schofield & Gubbels, 2019).

- Transferable vulnerability: A driver that shifts vulnerability from one place/citizen to another, or which reduces the vulnerability of one place/citizen and increases the vulnerability of another. Example: Air conditioning lowers the temperature of the inside of a building, making its residents less vulnerable to heatwaves. However, it also increases the temperature outside of the building, worsening the urban heat island and therefore increasing the vulnerability of all that need to be outside (e.g. for work or transport Dimitrova et al., 2021; Luo et al., 2020; Kim & Ryu, 2015). Air conditioning was also found to have detrimental effects on other – passive – cooling techniques (Hatvani-Kovacs et al., 2016).

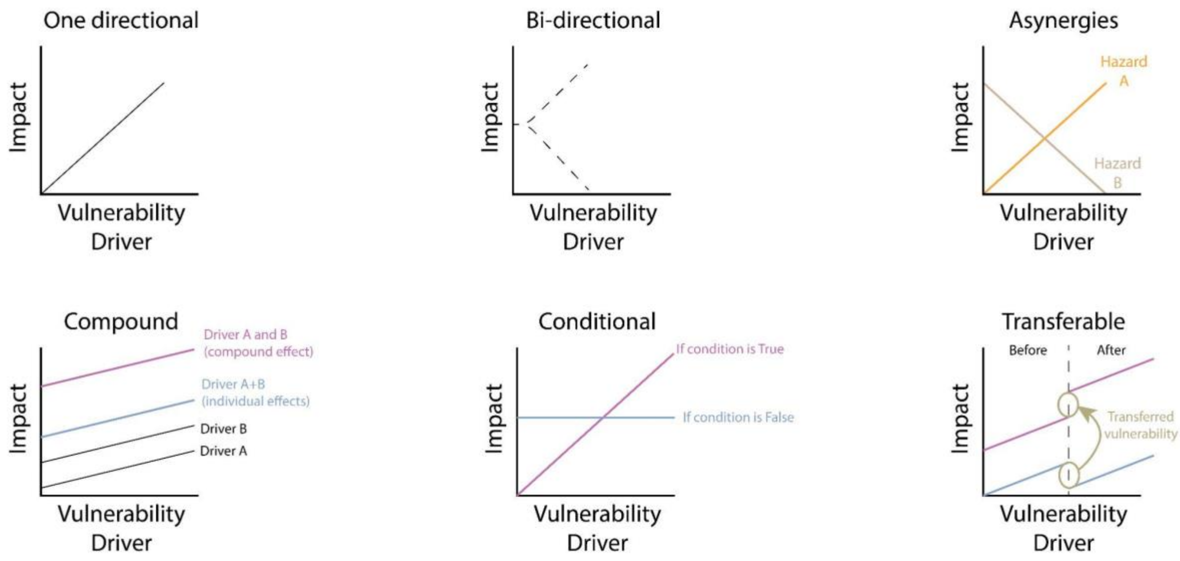

Figure 7: Schematic drawings of the directional and driver-interaction dynamics of vulnerability.

3.3 Statistics and machine learning techniques

This section outlines the different methods that have been identified, analysed, and applied by MYRIAD-EU to assess different aspects of the dynamics of multi-risk. Below, we provide detailed outlines of the following methods and approaches:

- Novel data streams such as Google Trends and newspaper articles
- Nighttime light satellite data and statistical difference-in-difference analysis
- Machine Learning and Artificial Intelligence

3.3.1 Novel data streams & statistics to understand impact-relevant extreme event durations

Overview

Various research and operational communities have developed approaches to quantify climate extremes in relation to their specific sector. An example of such hazards is heatwaves, which can be characterised by intensity or duration. However, many definitions emphasise intensity through percentiles or absolute values, while duration is either missing or considered as a secondary aspect. Duration is important to consider as it has been shown to contribute to the magnitude of the resulting impacts. Previous literature has found that longer heatwaves intensify societal impacts (Vogel et al., 2020), ecosystem impacts (Flach et al., 2021; von Buttlar et al., 2018) and adverse health outcomes (Anderson and Bell, 2011). In addition, the duration of extreme heat may also play a role in the recovery of a system or sector following an event. To address these issues, an approach has been developed to identify a range of durations of climate extremes where impacts are most noticeable. The resulting impact-relevant durations can be compared between impact and response metrics to assess the possibility of establishing more universal classification schemes for extreme event durations. In the following sections, heatwaves are used to demonstrate the above methodology.

Research aim

The categorisation and classification of extreme climate events, such as heatwaves, vary across sectors, leading to challenges in making meaningful comparisons. Consequently, the assessment of impacts associated with these hazards becomes complex due to variations in event definitions and characteristics. To address this issue, a methodology needs to be devised to establish a timescale for studying climate extremes that is based on the duration or length at which the majority of impacts are observed, providing a standardised approach for assessing and analysing the impacts of extreme climate events.

Input

The development and implementation of this methodology, as discussed in more detail in De Polt et al. (2023), involves the analysis of multiple data sources capturing different heatwave impacts and responses across sectors in Germany. In terms of public health, human mortality and heat-related hospitalisations are considered. For societal attention, Google searches of frequency and number of heat-related news articles are considered. These datasets are described in Table 3.

Table 3: List of datasets to determine impact or response from detected extreme events.

Variable	Sector	Spatial resolution	Temporal resolution	Source
Google Trends	Public attention	Country	Daily	Google
News articles	Public attention	Country	Daily	WiSo Factiva
Mortality	Health impact	Country	Weekly	Eurostat
Heat-related hospitalisations	Health impact	Country	Weekly	German Federal Statistical Office

Explanation of methods and workflow

The main methodological steps of the approach are shown in Figure 8, and in brief, the approach consists of: (1) data collection; (2) impact and response data processing; (3) identifying extreme heat events from the underlying daily mean temperature data; (4) examining the daily impact and attention anomalies within each event; (5) aggregating the daily anomalies for each event; and (6) repeating above steps for all events of all lengths.

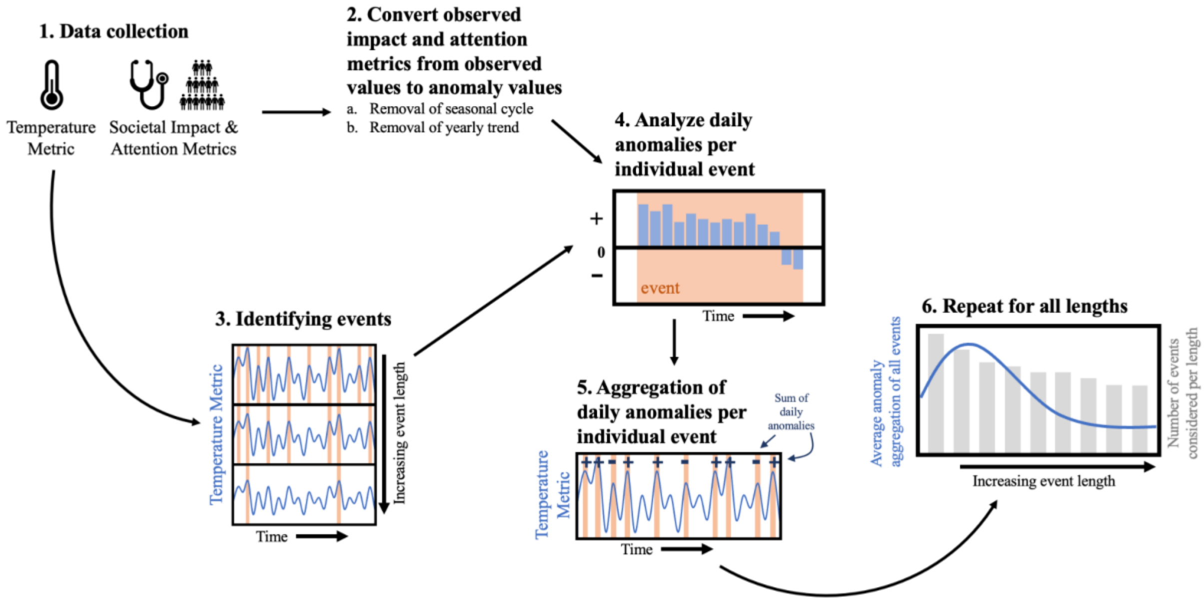

Figure 8: Schematic summary of the workflow. For each time scale, we find the hottest periods (between 1-day and 90-days; incrementing in daily intervals) and aggregate the related heatwave impacts or response for each considered data stream in order to identify the most impact-relevant time scales.

- The first step in this process is to derive moving average time series for each time scale of interest considered, in this example 1 day to 90 days. This is done by taking the mean of 1-90 days from each individual day of the time series and assigning it to that particular day as the day of onset of the event. (See time series; Figure 2). Second, from the moving averages of all time scales, we find the 90th percentile of all individual values separately for each time scale (see grey dashed lines; Figure 2). Finally, events are identified for each time scale by repeatedly: (i) findi^{ng} the hottest day of each time series (e.g., the day with the peak temperature of that event); (ii) excluding the 30 days around it to ensure independence between detected heatwave events; and (iii) finding the hottest value of the remaining time series. Steps (i)-(iii) are repeated to detect further heatwave events until the detected hottest temperature value of the observed time series does not exceed the 90th percentile of the initial time series after the moving average procedure (see grey vertical bars; Figure 8). Disregarding the 30 days around the peak in the temperature metric for each event allows more events to be considered within our sample size.
- The second step is the analysis of daily anomalies per event. Anomalies are created by converting each day's impact or response metric value from the observed value to a seasonal anomaly by removing the seasonal cycle (i.e., week number average).
- Step three is aggregation of the daily anomalies per individual extreme event. To relate societal attention and health impacts to heatwave duration, we aggregate daily anomalies from the societal data sources over a time window equal to the length of the heatwave under consideration. Anomalies are used instead of raw values because they represent a deviation from baseline or expected values. We assume that people, and human and environmental systems, are largely adapted to baseline conditions, as expressed by the mean seasonal cycle, and are therefore less prepared for deviations from this baseline. Positive anomalies imply a more pronounced response than normal and vice versa. Ultimately, we are interested in the length of heatwaves that produce a more pronounced response, indicated by a larger positive anomaly over the entire event. This methodology is achieved by adding all observed anomaly values for the

length of the event (i.e., 1 day has 1 anomaly value; 2 days add the anomaly values of day 1 and day 2), which allows positive anomalies to accumulate and negative anomalies to subtract from the overall values. This is repeated for all societal metrics and heatwave lengths. Having completed the previous step, we then compare between event lengths (step 4 in Figure 1). The mean of all aggregated daily anomalies of all events of the same length is then calculated, producing a single value, which is then related to the length of the heatwave.

- The above steps are then repeated for all lengths. Then the durations can be compared to find the length with the largest average daily aggregated anomaly.

Novelty of methods

This methodology has been used to address the gaps and limitations in the current quantification or identification of extreme events. For example, heatwaves can be explicitly explained in terms of intensity and duration. As most definitions emphasise the intensity of these hazards through percentiles, duration is either missing or a secondary aspect in current definitions. In particular, the duration of heatwaves is an important characteristic to consider, as it has been shown to contribute to the magnitude of the resulting impacts. These percentiles or thresholds have been defined in a variety of ways in the literature, resulting in events with the same name being classified or measured in different and potentially incomparable ways (Seneviratne et al., 2021).

(Expected) outcomes

The findings of this study have provided insights into useful time scales at which extreme event characteristics can be aggregated. An impact-relevant duration is needed to accurately define and determine time-dependent intensity-damage functions or hazard-impact thresholds.

Conclusions

This finding highlights the relevance of making informed choices on the considered time scale in heatwave analyses. The approach we introduce here can be extended to other societal indices, countries, and hazard types to reveal more meaningful definitions of climate (impact) extremes to guide future research on these events. An improved understanding of weather and climate hazards with their impacts on society, economy and environmental systems will support better preparation, response, and future adaptation.

3.3.2 Nighttime lights & statistics to understand recovery after single- vs. multi-hazard events

Overview

While recovery can be significantly different in a multi-hazard context in comparison to a single-hazard context, no quantitative studies have explored the general differences in recovery between single- and multi-hazard events (see section 2.3). Here, an innovative methodology is proposed to elucidate general patterns in single- vs. multi-risk recovery, analysing a large number of disaster events on a multi-continental scale. For this purpose, the suitability of using Nighttime light satellite data in combination with statistical approaches has been explored.

Various different types of satellite data have been previously used to analyse post-disaster recovery. Past studies have for example used satellite images to track the number of reconstructed buildings in a disaster-stricken area or the presence of vehicles on roads, as a proxy for the state of transportation and road functionality, or to identify (non-)collapsed and blue tarp-covered buildings (Brown et al., 2012; Ghaffarian et al., 2020; Miura et al., 2020). Other studies have used land use and land cover data (e.g., Sheykhmousa et al., 2019) or vegetation proxies (e.g. Ryu et al., 2018) to assess post-disaster recovery. Nighttime light (NTL) satellite data are a commonly applied recovery proxy to study economic recovery after disaster occurrences. It has for example been applied by Gillespie et al., (2015) to study damage and recovery after the Indian Ocean Tsunami in 2004, and by Gao et al. (2020) to analyse the economic recovery after the 2015 earthquake in Nepal. It has also been previously applied to analyse a set of hazard events with the aim of elucidating general recovery trends. For example, Barton-Henry & Wenz (2022) used monthly NTL data in combination with a difference-in-difference (DiD) analysis to study hurricane recovery for 7 major hurricanes in the USA. NTL satellite data captures various light sources that are present at night, including moonlight, directly emitted light (e.g., by buildings or streetlights), and reflected lights.

Research aim

The general aim of this research is to find patterns and differences in the recovery dynamics (i.e., duration, rate) after single- vs. multi-hazard events. This study uses NTL satellite data and a DiD statistical analysis to characterise and compare economic recovery for single- and multi-hazard events in the USA, Europe, and Asia.

Input

The newest generation of NTL data are recorded by the Visible Infrared Imaging Radiometer Suite (VIIRS) satellite. These data are processed both by NASA (Black Marble) as well as NOAA and available with a 500m resolution as cloud-free composites, on a daily, monthly, and yearly basis (2012-present). For this study the daily NASA Black Marble data (VNP46A2) has been found most promising, as its daily temporal resolution provides the opportunity to assess short term recovery patterns after disaster events. Pre-processing of this data by NASA includes a correction for stray-light, moonlight presence, lunar reflectance, and for snow, seasonal, and atmospheric effects (Román et al., 2018).

To indicate hazard-affected areas and separate single- and multi-hazard events, the hazard data of the MYRIAD-HES (MYRIAD Hazard Event Set) dataset (Claassen et al., 2023) are used, which can be adapted using more recent data or locally available data of improved quality. MYRIAD-HES is a database of multi-hazard event footprints, derived using the MYRIAD-HESA (MYRIAD Hazard Events Sets Algorithm) in combination with single-hazard footprints). The hazard types that are included in this study are those whose impacts and recovery are known to be captured in NTL data (i.e., storms, floods, tsunamis, earthquakes, and potentially landslides). The Global Human Settlement Layer Degree of Urbanisation (GHS-SMOD) dataset is used as a measure of exposure, to focus the analysis on urban areas, where NTL data are known to better represent changes in economic activity than in rural areas (Gibson et al., 2021; Pérez-Sindı́n et al., 2021; Schiavina et al., 2023).

Explanation of methods and workflow

A statistical approach that has been identified as well-suited for elucidating the effect of single- versus multi-hazard events on the NTL data is the DiD analysis. By comparing the pre- and post- intervention values of a region of interest (first difference) to the pre- and post- intervention values of an unaffected control region (second difference), a DiD can help distinguish which changes in the value in the region of interest are attributable to the intervention (i.e. in this case the hazard event). The DiD method assumes that the values in both areas would follow the same trend without the intervention. The versatility of this method allows its application to a wide range of topics. It has already been successfully employed in studying recovery following disaster events, as demonstrated by Barton Henry & Wenz (2022).

The workflow that has been set up to answer the research question is outlined in Figure 9. Starting from the NTL data (1), further pre-processing steps are necessary to be able to use the data in the analysis (2). This includes the selection of only good-quality pixels that represent urban area, using the mandatory quality flags that are included in the Black Marble data (Román et al., 2018) and the GHS-SMOD dataset (Schiavina et al., 2023). Pre-processing also entails the removal of additional unwanted light sources, such as lights from fires, using the (dynamic) fire Global Wildfire Dataset that is included in MYRIAD-HES (Artés et al., 2019; Claassen et al., 2023). As daily NTL data are used, there can be a lack of data due to cloud coverage on specific days, especially problematic when the hazard event is associated with significant cloud coverage. As a solution, the data are aggregated to weekly composites, providing more coverage than daily data while preserving the short-term insight in recovery dynamics. Using the hazard polygons (3), affected NTL pixels are identified per single- or multi-hazard event (4). For single-hazard events the whole geometry is used, while for multi-hazard events only the area affected by multiple hazards is considered affected. For each affected pixel, reference pixels are selected based on time-series similarity, to ensure consideration of heterogeneity in NTL pixels (Lhermitte et al., 2010; Veraverbeke et al., 2012). To be able to compare truly single-hazards to multi-hazards, regions affected by other hazards (not included in the event of interest) are not considered in the analysis. Then, per event, the DiD analysis is performed (5), comparing the difference in NTL in the affected cells with the NTL values in the unaffected control cells. The results for single- and multi-hazard events are then compared, to determine if there are any general patterns in recovery dynamics for single- vs. multi-hazard events (6).

<u>Novelty of methods</u>

This study contributes to the generally under-studied field of multi-hazard recovery. Where the limited number of previous quantitative multi-hazard recovery studies were highly localised and specific (see section 2.3), the proposed methodology uses previously successfully applied data sources and statistical approaches to unveil more general patterns in recovery for single- vs. multi-hazard events. With regards to the use of NTL as a proxy for recovery, the main novelty of the proposed methodology lies in the adoption of a multi-hazard perspective. To the best of our knowledge, analysing both single- and multi-hazard events and taking into consideration what the effect is of additional hazards that have occurred has not been previously done using NTL data, nor other satellite recovery proxies. Previous studies that used NTL as a proxy for post-disaster recovery have only focused on single-hazard events, generally not accounting for the occurrence of additional hazards (e.g., Barton-Henry & Wenz, 2022; Skoufias et al., 2022). Moreover, previous studies that analysed a large number of events using NTL satellite data, aiming to investigate general trends, were not only focussed on single-hazard events, and were also limited to monthly or yearly NTL data (e.g., Barton-Henry & Wenz, 2022; Felbermayr et al., 2021). The use of the daily Black Marble data allows for new insights into short-term patterns.

<u>(Expected) outcomes</u>

Per single- and multi-hazard event, the methodological approach (Figure 9) yields information on the post-disaster %NTL intensity in the disaster-affected area in comparison to what would be expected based on the control pixels, per time step for a fixed period after the disaster. These individual results can be combined into average values per time step for single- and multi-hazard events separately, providing insight into recovery duration and speed of both event types.

<u>Conclusions</u>

A novel methodology has been identified to use NTL satellite data in combination with a DiD statistical analysis to analyse a large number of single- vs. multi-hazard events, with the aim to provide insights into recovery patterns after both event types. An improved understanding of how recovery dynamics can be different after multi-hazard events in comparison to single-hazard events is essential for multi-risk assessments and the design of appropriate DRR strategies, specifically for post-disaster response and recovery.

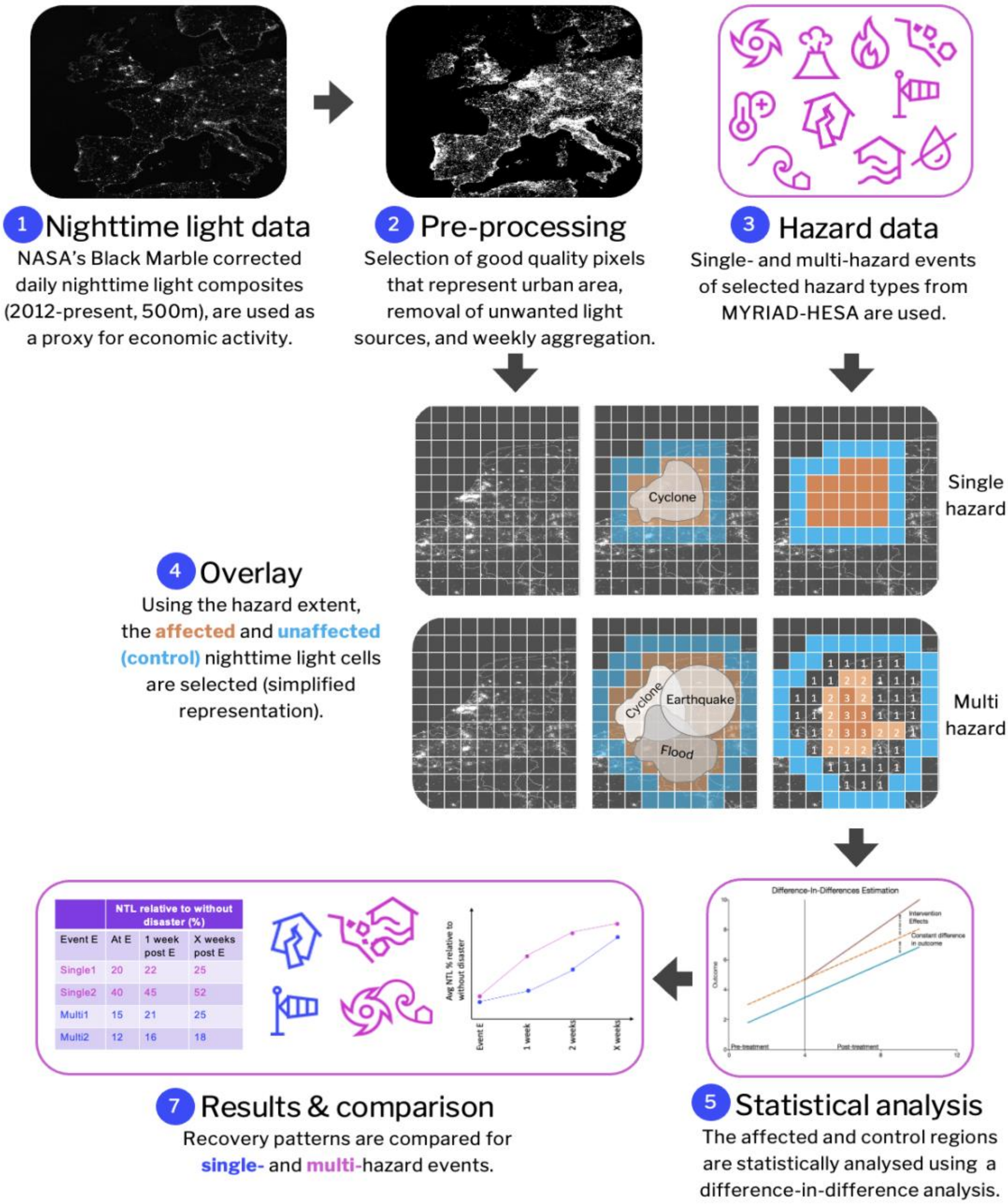

Figure 9: Step by step workflow for proposed methodological approach of applying DiD to study changes in NTL values post-disaster, for a large number of single- and multi-hazard events.

3.3.3 Machine learning for understanding dynamics of risk drivers

Overview

Machine learning, a subset of artificial intelligence, utilises algorithms to interpret complex data patterns and it can be applied to the exploration of multiple risks from climate change. These methods have been mainly explored for their application to the Veneto pilot. Machine learning applications excel at leveraging big volumes of heterogeneous data coming from different sources to investigate spatio-temporal dynamics of the multi-risk events and their impacts. The methodology will focus on learning from past multi-hazard interactions, identifying the main hotspots, trends, and characteristics of multi-hazard events, in order to produce a risk estimate associated with multi-hazard events and extract the most important risk factors in the case study area. A forward-looking assessment is also planned: by feeding future projections of different climate change scenarios to the previously trained (on historical data and impacts) model, the evolution of future multi-risk scenarios will be analysed.

Research aim

The aim of the research is to use machine learning and data driven methods to analyse multi-risk events in the Veneto region, through the analysis of historical records and future projections, considering different climate change scenarios. More specifically, machine learning applications will facilitate the analysis of the relationships between risk factors acting at different spatial and temporal scales, and across different landscapes (such as the coastal areas, plains and mountains that are part of the Veneto region). Moreover, impacts on different sectors will be considered, including environmental impacts on water quality, air quality and vegetation, and impacts on socio-economic systems (such as on population, buildings, infrastructures).

Input

To analyse the complex and multi-faceted interactions between hazard, vulnerability and exposure factors characterising multi-risk events, hazard, vulnerability and exposure indicators are used as input features, while historical impact data are used as assessment endpoint and labels for the training of supervised machine learning methods.

Hazard data describe climate and meteorological indicators, such as temperature, precipitation, wind, soil moisture, sea level. These can be further divided into several categories, such as observations (such as real weather data from monitoring stations), climate reanalysis (data combining past observations with models to generate consistent, gridded time series of multiple climate variables) and climate projections that describe the future evolution of climate variables, under different climate change scenarios. Examples of hazard datasets are CERRA (Copernicus European Regional ReAnalysis), which provides meteorological variables for the atmosphere and the surface every 3 hours and at 5.5 km resolution for Europe; ERA-5, produced by Copernicus and ECMWF which provides hourly estimates of a large number of atmospheric, land, and oceanic climate variables at 30 km resolution for the whole globe. With regards to future climate projections, different Euro-Cordex models downscaled for the Veneto region or models developed by CMCC for the North Adriatic or Italian region (such as Climate Projections RCP4.5 and RCP 8.5 downscaled @2.2 km over Italy) have been explored in the Veneto pilot.

Vulnerability and exposure data provide information on the territory and topography, the susceptibility to certain hazards and the socio-economic and environmental characteristics of the area under analysis. Examples of such data are topographic information (elevation, slope, distance to sea or rivers, etc.), soil characteristics (permeability, subsidence, etc.), land use and land cover data, population characteristics (density, gender, age, etc.), presence of critical infrastructure (roads, airports, hospitals, etc.), urban, natural or cultural areas (e.g., presence of UNESCO world Heritage sites), and economic activity (e.g., presence of buildings linked to specific sectors). This information can be retrieved from European datasets, such as EUROSTAT, providing statistical information on socio-economic activities in Europe, or more local datasets such as ISTAT for the Italian territory, and regional datasets developed by the Veneto region (see D3.3a, appendix for Veneto pilot for more information on the datasets used in each pilot). Moreover, satellite images can be processed to gather vulnerability and exposure information, such as for vegetation conditions and land cover characteristics. Indicators from vulnerability and exposure, will be fed into machine learning supervised models together with the hazard ones to analyse the impact of past single- and multi-hazard disasters. The availability of vulnerability datasets covering multiple years (if possible, before and after the occurrence of a hazard) will allow for the investigation of vulnerability changes and their influence on multi-risk impacts.

Impact data for multi-risk events are catalogues describing losses caused by historical extreme weather and climate events. These can be Boolean datasets, only describing the occurrence or non-occurrence of impacts in a defined area or sector; qualitative, providing a high-level description of the impacts or quantitative, expressing a monetary cost of the impacts. The accuracy and precision of the impact datasets is key for the robustness of the machine learning models, since any bias in the impact data used for training would be propagated and amplified in the rest of the analysis. Examples of impact datasets that are envisioned for machine learning applications are the ESWD (European Severe Weather Dataset), data from the catalogues of emergency situations in the Veneto regions, data on river water quality from monitoring stations deployed by ARPAV, and vegetation condition data from Copernicus (or similar) datasets (see also section 3.1.1).

<u>Explanation of methods and workflow</u>

The main categories in which machine learning algorithms are usually divided are supervised or unsupervised machine learning. Supervised machine learning is typically employed when past events data are available, and the aim of the analysis is to create an analytical relationship between a set of labelled inputs and a set of outputs. A labelled dataset is a set of data with input (usually called features or indicators, in risk assessment application they represent the risk drivers) and the corresponding outputs (labels or assessment endpoints, in the case of risk assessment application they can be the recorded impacts) (Russell & Norvig, 2016). Unsupervised machine learning algorithms instead aim at learning patterns and structures from raw (unlabelled) data: they can be used to build compact internal representation of the data (dimensionality reduction), clustering, and to generate synthetic data similar to the analysed samples.

In the following section a selection of machine learning methods envisioned to be tested within MYRIAD-EU is presented. This is just a first analysis of the possible methods that can be tested: the final methods to be applied will be decided in collaboration with the Pilots' teams, depending on the data availability and the research questions each case study will prioritise.

Clustering algorithms aim at producing a partition of the data that can be used as a basis for further analyses. For example, DBSCAN, is a clustering algorithm that has been applied to identify the spatio-temporal clusters of hazards, such as extreme precipitation, extreme wind (Tilloy et al. 2022), drought, and heatwaves (Yu et al., 2022). Starting from data of gridded climate anomalies (identified through percentile or empirical thresholds, explained in section 3.2.2), the clustering techniques can be used to group single-event anomalies in time and space to create single-hazard clusters. These can be analysed to extract intensity, area covered and seasonality of the events and combined to identify compound or cascading multi-hazard clusters, for example applying the algorithms developed within Task 5.1 of MYRIAD-EU, i.e., the MYRIAD-HESA methods for the generation of a multi-hazard event set (Claasen et al., 2023). The main advantage of DBSCAN for multi-hazard footprint identification, compared to other clustering algorithms such as K-Means, is that it doesn't require to know in advance the number of clusters analysed, but is able to extract any number of cluster analysing areas of high/low density of the data. Moreover, the shape of the clusters need not be convex.

Decision trees and ensemble methods. Decision trees popularity is due to their easy implementation (thanks to specific python libraries, such as sklearn (https://scikit-learn.org/stable/modules/tree.html), which provide several ready to use implementations) and their interpretability. In fact, the features which are more important for the learning tasks are identified and form the first level of the decision tree. However, decision trees often present overfitting: the model is learning noise and is not able to generalise to new unseen data. Other methods, based on decision trees are now more popularly implemented in risk assessment tasks: Random Forest is based on the construction of many decision trees from a randomly selected sample of training data and features (Zennaro et al., 2021), which allow them to be more robust against overfitting (a limitation of traditional decision tree models). Compared to other decision ensemble learners, Random Forest uses bagging techniques to combine the output of the single decision trees. This method, also called Bootstrap Aggregation, combines results from multiple decision trees trained in parallel, each taking into consideration only a subset of sample data. Other algorithms (such as XGBoost) instead use boosting techniques, in which the single decision trees are combined sequentially, with each new iteration focusing on misclassified observations of the previous one. The boosting methods offer higher predictive accuracy, but at the expense of higher computational costs. Both are popular in climate risk assessment applications thanks to their interpretability: it is possible to extract the variables that most contribute to the final model through feature importance techniques. An example is in Park et al. (2020), where Random Forest (together with other supervised machine learning algorithms) is used to estimate present and future risk of coastal flooding in South Korea or for forest fire susceptibility assessment using Google Earth Engine (Piao Yong, 2022).

Support Vector Machines (SVM) are supervised learning models mostly used for classification tasks. The algorithm maps training examples to points in space to maximise the width of the gap between the two classes. New examples are then mapped into that same space and predicted to belong to a class based on which side of the gap they fall. They excel at non-linear classification tasks: in fact, if two classes can be separated with a linear function (i.e., a line or a hyper-plane, depending on the dimension of the data), the classification is said to be linear; if a nonlinear function (such as a curve) is needed, the classification task is non-linear. SVM can perform non-linear classification using the "kernel trick", which implicitly maps non-linearly separable inputs into high-dimensional feature spaces where the boundary between the classes is linear. SVM are thus widely used as benchmarks to compare the performance of other machine learning models. Some examples of their use are in storm surge flood susceptibility assessment (Sahana, 2020) or for forest fire prediction (Singh, 2022).

Neural Networks

Multi-Layer Perceptron (MLP): MLP is amongst the simplest neural networks: an MLP consists of at least three layers of nodes: an input layer, a hidden layer and an output layer. They are feedforward neural networks, i.e., the data flows from the input layers to the output layers, passing through the nodes that perform matrix multiplications (each node is associated to a weight that controls its contribution to the overall result) and apply non-linear functions (called activation functions). A technique called backpropagation is used to train the neural network, which aims at updating the weights associated to each node to minimise the error between the score produced by the output layer and the expected result.

The non-linearity of the activation function allows the MLP to be a universal approximator, i.e., it can (theoretically) model any function, given a large enough training sample. It is most suited to model complex-linear functions between high-dimensional data. However, more advanced techniques are needed if specific temporal or spatial patterns are to be extracted from data, such as convolutional neural networks or recurrent neural networks. In fact, the MLP does not consider the spatial structure of the data or the order of the training samples, but analyses one sample at a time, independently from the others. It is thus necessary to create a dedicated variable to explore time and spatial dependencies, (i.e., a variable for describing the wind speed at a 7-days lag-time, or a variable calculated over a specific distinct area). This can be unfeasible if the specific lag-times or spatial influences are unknown and, even if they are known, it can lead to the creation of an excessive number of variables, which will reduce the performance and robustness of the model. The MLP is still thoroughly applied for natural hazards and risk assessment, often as a benchmark for more complex neural networks, such as for flood susceptibility mapping (Ahmadlou, 2020).

Convolutional Neural Networks are a type of feedforward artificial neural network that use a mathematical operation called convolution in place of general matrix multiplication in at least one of their layers. One of their distinguishing features is their ability to extract spatial features by enforcing a local connectivity pattern between neurons of adjacent layers. They have been successfully applied to extract features from images, such as extracting flooded areas from satellite images, (Wang et al., 2020), but also to identify and classify different extreme weather events (Liu et al. 2016).

Recurrent Neural Networks are a class of artificial neural networks that allow the analysis of sequences of data, adaptively modelling temporal dynamic behaviour. This makes them applicable to tasks where there are factors acting at different timescales (such as a combination between slow onset processes and extreme events). LSTM have been used for example to analyse surge predictions in coastal areas (Tiggeloven et al., 2021) or memory effects on vegetation (Kraft et al. 2019).

Novelty of methods

The application of machine learning to multi-risk assessment is an emerging and dynamic area. In particular, the main novelties focus on:

- Developing Integrated Risk Models. Advances in creating integrated risk assessment models that can handle multiple types of risks. This involves developing machine learning algorithms capable of considering various risk factors, such as economic, environmental and social factors, and assessing their combined impact on a given scenario.

- Data fusion and integration. As the volume of data from various sources continues to grow, effective data fusion and integration techniques become more important. Machine learning approaches can combine heterogeneous data sources like satellite imagery, social media data, climate models data, and more, to provide a comprehensive view of multiple risks.
- Complex Relationship Recognition: Machine learning techniques, and in particular deep learning, are employed to recognise complex relationships between different risk factors and model spatio-temporal dynamics at different scales. These techniques can help capture non-linear interactions and dependencies that could lead to unforeseen risks.
- Interpretability and explainability: Interpretability of machine learning models is vital in risk assessment to understand why a certain prediction or decision is made. Decision Trees and Ensemble methods offer techniques that allow for the identification of the most important risk indicators, and newly developed explainable frameworks for deep learning, such as SHAP (https://shap.readthedocs.io/en/latest/) or LIME (https://towardsdatascience.com/lime-explain-machine-learning-predictions-af8f18189bfe) are helping the interpretation of the most complex models.

Expected outcomes

The general outputs that the machine learning methods can provide are:

- Single- and multi-hazard clusters, analysing their hotspots and trends, combining statistical and unsupervised machine learning methods.
- A risk assessment model trained on historical data, able to estimate the risk associated with different hazards and able to model impacts caused by processes acting at different time and spatial scales, obtained through the application of an ensemble of supervised machine learning techniques.
- A ranking of the most important features for multi-risk assessment will be derived from the supervised machine learning model, taking into account hazard, vulnerability, and exposure factors. Depending on the method used, a feature importance extraction or a sensitivity analysis will be carried out.
- The estimate of future risk under (different) climate change scenarios, highlighting the impacts caused by different combinations of risk drivers, produced by applying supervised machine learning models on future climate (and exposure/vulnerability) projections.

Conclusions

Machine learning models excel at unravelling the complex dynamics of multi-risk events and disentangling the effects of different risk factors. However, the availability of accurate impact data from past multi-risk events, high resolution hazard, vulnerability, and exposure information, to be used for training, may limit their applicability.

3.4 Disaster forensics analysis on paired disasters

Disaster forensic analysis refers to the systematic examination and investigation of past disasters to understand the causes, factors, and dynamics that contributed to their occurrence and impacts (Keating et al., 2016). It involves assessing various aspects of the disaster, such as physical damage, social vulnerabilities, response efforts, and recovery processes. By conducting thorough forensic analysis of disasters, we can gain valuable insights that contribute to a better understanding of disaster risk.

So far, many disaster forensic analyses have focused on comparisons between single-hazard types across space and/or time (e.g., Kreibich et al, 2022; Borga et al. 2019). Building on the work by Kreibich et al. (2022), MYRIAD-EU put out a global call for multi-risk case studies. Using the community-wide contributions, MYRIAD-EU has developed a global database of 160 examples of past multi-hazard event pairs from across the globe, including geophysical, meteorological, and hydrological hazards, and that happened within the past 40 years. A core team of researchers has been put together who will lead the data collection process. To this end, first a template has been developed and tested by non-MYRIAD-EU contributors. This template will be used to collect data from all case studies: all contributors will be asked to complete the template providing detailed information about their case study on for example, multi-hazard type characterisation, description of dynamics of risk elements, and the role of DRR measures. Upon completion, this database will be used to assess challenges for DRR in the context of multi-hazard risk. The analysis will aim to provide a better understanding of (a)synergies of DRR measures between hazards and aims to collect good practices and bottlenecks for DRR in a multi-hazard context. Finally, this database can also be used to improve our understanding of how risk factors change in between and after multiple disasters and specifically the role of local (socioeconomic vulnerability) conditions relating to disaster impacts.

3.5 Dynamic vulnerability: consecutive occurrence of disasters and disease outbreaks

Recently, the disaster risk field has made substantial steps forward to develop increasingly comprehensive risk assessments, accounting for the incidence of multiple hazards, trickle-down effects of cascading disasters and/or impacts, and spatiotemporal dynamics. While the COVID-19 outbreak increased general awareness of the challenges that arise when disasters from natural hazards and diseases collide, we still lack a proper understanding of the role of disease outbreaks in disaster risk assessments and management. The UNDRR (2020, 2022) and the World Health Organisation (WHO, 2019) underscored the urgency to understand changing socioeconomic vulnerability due to the interactions between disasters and subsequent disease outbreaks (Fig. 10). Several studies have shown that natural hazards can contribute to changing vulnerability to waterborne disease outbreaks by, for example, impairing access to clean Water, Sanitation and Hygiene (WASH-)infrastructure, and increasing chances of infectious-disease spreading in refugee-facilities (Jones et al., 2020; Mora et al., 2022). Geophysical disasters can also damage sanitation infrastructure, triggering waterborne disease outbreaks (Jutla et al., 2017). Research suggests that the probability of a disease outbreak following a hazard is influenced by underlying dynamics of socioeconomic vulnerability (Mazdiyasni & AghaKouchak, 2020). Finally, an understanding of the effects of different time-lags between hazards and disease outbreaks (ranging from days to months) is necessary to respond effectively, but is currently lacking. Therefore, MYRIAD-EU will make use of existing data including MYRIAD-HESA (Claassen et al. 2023), disease outbreaks, and global vulnerability data, and existing methods such as multivariate statistics and Dynamic Bayesian Networks to explore this novel field of research and to specifically look into vulnerability dynamics across different groups (e.g. elderly, female).

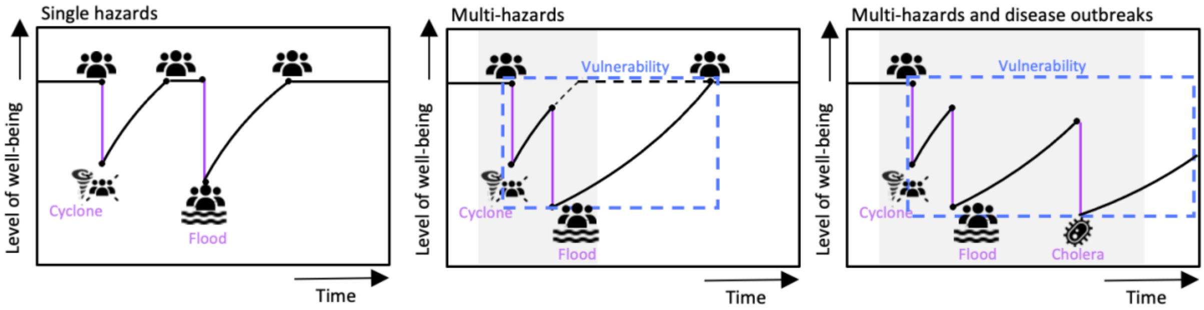

Figure 10: Stages of growing understanding of increasing disaster-risk complexity from single-hazard thinking (left panel), to multi-(hazard) risk thinking (middle panel), to including disease outbreaks (right panel). The important role of vulnerability acting as a multiplier is demonstrated by the changing slope of the level of well-being after disasters and disease outbreaks.

4 Challenges & opportunities

In this section we describe our key observations in terms of challenges and opportunities related to well-established and novel data sources as well as methods and their suitability for detecting dynamics and feedbacks of risk drivers and applicability to local case studies.

4.1 Datasets

We have reflected on different datasets: currently existing datasets and novel data sources that have been identified. Below we discuss the key opportunities, challenges and limitations that have been identified.

4.1.1 Traditional data sources

Existing data sets can be grouped based on their local-to-global availability.

4.1.1.1 Local & regional

Historical hazard data are typically available with high resolution and long timeframes (there are climate reanalysis datasets available for Europe with time series of more than 40 years of hourly data, with spatial resolutions of a few kilometres per cell). However, using this data for future hazards can pose challenges due to the required generalisation of the models: especially when applying machine learning or statistical models trained on historical data to future projections these need to have a similar statistical behaviour, at least if analysed on the same period (i.e., comparing the historical data to a baseline scenario of the models, covering the same timeframe). Most often, climate reanalysis or observations have different statistical distributions than the modelled data due to the impossibility to represent all the physical processes. In particular, indicators describing extreme events, which are key for risk analysis, often have different ranges and characteristics (for example precipitation events may be more frequent but less intense in future projections) reducing the ability of the model to predict accurate future risk scenarios. Traditional bias-correction techniques often do not solve these problems because they are focused on adjusting averages of the variables between future and historical data and are not tailored for correcting the tails of the distributions. Specific bias-correction methods, such as quantile mapping, are thus needed to align the two datasets before the application of statistical or machine learning methods.

Vulnerability and exposure data usually have a much coarser temporal resolution than hazard data, with many data sources presenting only monthly or yearly data. This difference in resolution makes it very hard for the model to learn the role of vulnerability and exposure factors and may limit the ability to model these factors dynamically.

The integration of impact data can present certain difficulties to machine learning, particularly due to the sparse nature of multi-risk events that are predominantly linked to extreme weather. This sparsity poses a unique challenge for machine learning, especially for classification tasks that demand specific methods like oversampling, under sampling, or weighting to counterbalance disparities between classes.

The accuracy of the past impact data is also fundamental to correctly identify the right relations between the risk drivers: if the training datasets presents spurious or inaccurately labelled impacts, these errors will be propagated further and amplified through the analysis. A lack of precision in the localisation of an impact (i.e., an area damaged by flash floods) may impair the ability of the model to link this event to a specific risk factor (such as permeability of the soil) that has a great spatial variability but had to be aggregated over a wide area in order to comply with the coarser resolution of the impact data. Moreover, an impact dataset which is not consistent over time (most local impact datasets do not have clearly defined parameters and are subject to the personal interpretation of the person/association analysing the events) may result in biased models.

Multi-risk assessment poses further challenges because there is a lack of impact catalogues specific for multi-risk events (most of the studies have been dealing with just one hazard at a time), so performing supervised machine learning may require additional pre-processing steps to correctly identify and label past multi-risk impacts.

4.1.1.2 Global

The EM-DAT data set gives limited opportunity for statistical analysis and drawing conclusions due to the number of data points (events with full data) and data quality. A preliminary conclusion given the quality of the global dataset is that there are non-linearities in the hazard – impact relationship that might result from the interactions of multiple hazards. The limitations of EM-dat challenge getting accurate estimates of the characteristics of the risk drivers (exposure, hazard magnitude and vulnerability) and poses challenges to analysing their interrelationships and dynamic feedbacks.

In order to make the data set suitable for an in-depth statistical analysis of changes in losses and damages that arise from interactions between multiple hazards we recommend using additional data sources:

- for currently missing impact data
- for currently missing data on hazard intensities
- to standardise interpretation of impact variables “Total Affected” and “Total Damages, Adjusted (‘000US$’)” for consistency across events.

We also recommend investigating a wider definition of multi-hazard events, for example, consecutive events such as the tropical cyclone and earthquake in Haiti in 2019 and the two tropical cyclones making landfall in Mozambique in 2020 (see, e.g., de Ruiter & van Loon 2022).

4.1.2 Novel data sources

Below we summarise our key findings on opportunities, challenges, and limitations of novel data sources.

4.1.2.1 Nighttime lights (NTL) data

Opportunities

- Future releases of the Black Marble NTL data by NASA will include tools through which users can create a high definition 30m resolution version of the data, which would be useful for obtaining more detailed information about recovery of a single- or multi-hazard event on a more local scale (e.g., Román et al., 2019).
- NTL can provide a means to track recovery in areas where it is difficult to monitor or where there are no other data sources available.
- Satellite data are beneficial because they are uniform and globally available, allowing for a large-scale, long-time study to uncover general patterns in single- vs. multi-hazard recovery and the socio-economic factors that affect this.
- The use of NTL can aid in the construction of post-disaster recovery storylines for multi-hazard events.

- Locally there can be an opportunity to account for additional factors that can influence the NTL values, like technical blackouts or intentional preventive blackouts, if data are available.
- The general recovery characteristics found for single- vs. multi-hazard events and the factors that play a role could be used to include this aspect of dynamic vulnerability when looking into future events.

Challenges

- Defining NTL recovery as %NTL in comparison to the value without the disturbance does not provide insights into the specifics of recovery processes, e.g., building back better, people moving out or into the area, effect on resilience/adaptive capacity. For this we need information on more detailed post-disaster recovery indicators and monitoring thereof on short (days to weeks) as well as long (months to years) time scales. It is important that this is done in a consistent manner, to allow for comparison between different (single- and multi-hazard) events.
- NTL data capture light visible from space, meaning that lights like streetlights and billboards contribute for a large part to the total observed light intensity. After a disaster, the restoration of such non-essential light sources often lags electricity restoration for essential infrastructure (Román et al., 2019).
- There can be alternative reasons for NTL reductions that can affect the results, which cannot be accounted for using the current approach; e.g., blackouts due to technical problems.
- Cloud cover can be a big challenge. Especially when analysing natural hazards like tropical cyclones when there can be several days before, during, and after the disaster where NTL values are only available for a limited number of pixels. Additionally, daily NTL data are computationally heavy to process. This is why the choice has been made to aggregate to weekly instead.
- For some hazards, the impact is poorly captured by NTL data. Droughts, epidemics, extreme temperatures, and fog for example do not directly cause a NTL reduction. Also, explosive volcanic eruptions can produce significant volcanic ash clouds, and wildfires are accompanied with significant smoke development, literally clouding the data (Felbermayr et al., 2021, Zhao et al., 2018)

4.1.2.2 Google search interest, newspaper mentions, hospitalisations and mortality

Opportunities

- Google Trends Themes group the most relevant search terms around a theme (e.g., heatwaves as an extreme event) into a topic. This allows us to capture searches for multiple similar terms across languages, making the time series retrieved more meaningful than single terms.
- Google Trends data are an unbiased sample of Google search data. The data are also anonymised, categorised and aggregated.
- Google Trends data have only recently begun to be used in the natural sciences, although they have been used extensively across many disciplines (Jun et al., 2018).
- Previous analyses in the natural hazards field have found strong correlations between search frequency for the Google topic 'heatstroke' and heat stroke-related deaths and hospitalisations (Li et al., 2016). For other hazards, Google Trends data have been used to quantify awareness of drought (Kam et al., 2019; Kim, et al., 2019) and interest in earthquakes (Tan & Majarjan, 2018).

- Newspapers represent one aspect of societal attention, providing written evidence of diverse and difficult-to-quantify impacts related to climate extremes and natural hazards.
- Newspaper articles, both print and online, can serve as a source of hazard data or evidence, as well as a means of identifying the impact of these events. The text from these sources can be used in all forms of natural hazards research.
- Hospitalisations and mortality are used prominently throughout human health and climate hazard impact analyses.

Challenges

- The challenge in using hospitalisation and mortality data is the availability of data at both temporal and spatial scales. To obtain higher resolution data, one often must compromise on the spatial or temporal extent of the data. A common source of mortality data, Eurostat, publishes data on the number of deaths in different European countries disaggregated by week, age, sex and NUTS3 regions, although not all these disaggregated datasets are available for all countries. This is due to the availability of data from the source country, as data transmission is on a voluntary basis. Long time series are needed for robust comparisons over time and for statistical modelling.
- Challenges in using newspaper articles include the coverage of individual media outlets. Some media outlets may cover larger areas (i.e., country scale) compared to others that may focus more regionally (i.e., city scale). This can make it difficult to attribute the location of the hazard in question.
- Media coverage can also have an agenda-setting effect, with readers and other news organisations attributing greater importance and press coverage to things that receive more coverage.
- When using the content of news articles or media reports to analyse hazards, there may be instances where there is no verification or sources of misleading information. This does not affect the use of media to quantify public attention, although it should be considered when selecting news outlets for content analysis.
- The values obtained from Google do not represent the absolute search volume for a topic but are rather normalised and then indexed on a scale of 1-100.
- In some countries, for political or linguistic reasons, Google is not the primary search engine. This limits the ability to conduct analysis with the dataset globally.
- Some regions may have such a small population, or so few people using the search engine, that the noise level in the data becomes problematic for some analyses.

4.2 Methods and approaches

Below we summarise our key findings on opportunities and challenges of novel methods and approaches.

4.2.1 Differences in differences (DiD)

DiD is a well-established method that can be used in many different contexts, to find the actual effect of a disturbance to a system. Often, NTL recovery studies compare nighttime light values pre- and post- the disaster in a disaster-struck area (e.g., Schippers et al., 2022; Zhao et al., 2018; Román et al., 2019), but by taking the DiD the effect of additional factors that can be of influence is minimised.

Opportunities

- This method is applicable to the pilot regions, either to study recovery for a specific event or to elucidate general patterns like in this study.

- There are opportunities to improve the method locally by using:
  - locally available hazard data of better quality than the hazard data used in this study;
  - impact data/inclusion of a vulnerability component to determine the affected regions;
  - additional datasets to track (economic) recovery, on a high temporal and spatial resolution.

Challenges

- Results strongly depend on affected and reference regions chosen, and whether these fulfil the parallel trends assumption. Because of the large number of events and the large scale considered in this study, the affected regions are selected only using the hazard extent (hazard) and a degree of urbanisation map (exposure). However, preferably one would only look at regions that experienced actual impact, hence including a vulnerability component, but this is difficult at the scale of the current study. Additionally, regions that are unaffected by the hazards can still experience spillover effects that are unaccounted for in the current methodology (Felbermayr et al., 2021).

4.2.2 Quantifying impact-relevant durations

In order to make more informed choices about the time scale to be considered in extreme event analyses, a methodology has been developed to determine a range of impact-relevant durations. This methodology was developed and applied to a case study of extreme heat events in Germany (De Polt et al., in revision).

Opportunities

- The methodology for determining impact-relevant durations is applicable to any region, at any scale, as long as there are sufficient data to represent the hazard and the impacts of that hazard.
- This information can inform future research on climate hazards by suggesting useful timescales over which hazard metrics (e.g., temperature for heatwaves) can be aggregated for cross-sectoral impact research.

Challenges

- The applicability of this method is limited by the input variables available. This is particularly the case for impact metrics where availability may be limited. The methodology requires the spatial and temporal resolution of the hazard data to be equivalent.

4.2.3 Machine learning

Machine learning functionalities and capabilities, including high accuracy and adaptability, showed that machine learning can be considered as a promising tool for emerging studies on multi-risk assessment, allowing to analyse various extreme events occurring simultaneously or successively (i.e., compound, or consecutive events). Input data should consider all spatio-temporal variables characterising these types of complex events, describing their dynamics over time and projecting (and predicting) them under potential future scenarios.

Opportunities

- After training, the reliability of the Machine Learning model is typically checked through technical steps known as validation and testing. To ensure independence, the

data used for one step are not employed in any of the other steps; statistical techniques that take into account eventual correlation in the input data are to be employed to verify that the groups are as independent as possible, reducing their eventual correlation. Some examples are block-validation techniques, which exclude from the validation sets data which present spatial or temporal similarities with data used in training (Zanetti et al., 2022).
- The importance of an accurate impact dataset can be seen as an opportunity to establish monitoring techniques for building coherent and easily accessible impact datasets. The use of unsupervised machine learning may help in identifying past multi-hazard events and labelling data. Moreover, it can also be combined with other statistical techniques (such as copulas) to produce new synthetic multi-hazard datasets that can be used to reduce the training cost of supervised machine learning models.

Challenges

- The application of Machine Learning and Artificial Intelligence to multi-risk assessment is heavily dependent on data availability and quality. In fact, training supervised machine learning model relies on historical multi-risk events to learn the non-linear and complex relations between the risk drivers. These data need to have a high enough spatial and temporal resolution to be useful for modelling and the more sophisticated the model is, the more input data are needed for an accurate training. Moreover, a conspicuous number of multi-risk events is needed to train and validate such models.
- The spatial and temporal correlation of training data may reduce the robustness of the Machine Learning model and may pose challenges for validation and testing. In fact, ignoring the correlation between consecutive days or neighbouring areas when validating a model trained on climate data may result in underestimating errors and producing an overfitted model unable to generalise with new and unseen data.

4.2.4 Disaster forensic analysis

Disaster forensic analysis involves a methodical examination and investigation of previous disasters to comprehend the factors, causes, and dynamics that influenced their development and consequences. This process encompasses the scrutiny of diverse aspects related to the disaster, including physical destruction, societal vulnerabilities, emergency response endeavours, and the recovery journey. Through comprehensive forensic analysis of disasters, we acquire valuable insights that enhance our understanding of disaster risk.

Opportunities

- Disaster forensic analysis plays a vital role in enhancing our understanding of disaster risk by identifying root causes, assessing risk factors, evaluating response and recovery efforts, informing policy and planning decisions, and empowering communities.
- It provides valuable insights that contribute to more effective risk reduction strategies and the development of resilient societies.

Challenges

- Access to comprehensive and reliable data is crucial for conducting effective forensic analysis. However, in many cases, data collection systems may be inadequate or inconsistent, making it challenging to obtain accurate and detailed information about the disaster event, its impacts, and the contributing factors. Data gaps, inconsistencies, and biases can hinder the accuracy and completeness of the analysis.

- Conducting a thorough forensic analysis requires time, resources, and expertise. This time constraint may affect the depth and rigour of the analysis. Additionally, resource limitations can impact the scope and scale of the analysis, particularly in cases where multiple disasters occur simultaneously or in quick succession.

5 Conclusions

A better understanding and improved modelling capabilities of multi-(hazard) risk dynamics and feedbacks is needed to better inform DRR and adaptation strategies, and to support evidence-based decision-making. This requires the identification of data and methods capable of assessing these dynamics and feedbacks.

Several methods have been identified, explored, and tested to address the dynamics of risk and DRR measures. First, assessing vulnerability can be challenging due to its invisibility and variability. MYRIAD-EU's research enhances vulnerability assessments by studying time dynamics, impact relations, and vulnerability management. Through a systematic review we have compiled a database of urban characteristics of vulnerability. Monitoring these aspects over time reveals vulnerability dynamics, highlighting various vulnerability-impact relations. Next, extreme climate events, such as heatwaves, vary by definition, complicating sectoral comparisons. We have developed a novel methodology to study climate extremes based on impact duration and intensity using hospitalisation data combined with Google search and news article data. Thirdly, multi-hazard recovery differs from single hazard recovery. We are developing a quantitative methodology using Nighttime light satellite data to compare recovery after single- and multi-hazard events. This is a first step towards quantifying multi-hazard recovery. Fourthly, machine Learning and Artificial Intelligence have been identified as promising methods and are currently being tested to unveil patterns in complex data, supporting assessments for multi-risk events. Finally, we are using disaster forensic analysis to assess risk dynamics and the impacts of DRR measures using a database of historic disasters that has been developed in collaboration with the global multi-risk research community.

Next, MYRIAD-EU will further develop and test the identified methods in its pilots and local-to-global studies. These methods will be used to: support the software (to be developed in WP5), derive dynamic vulnerability functions (WP4), and feed into the database of empirical evidence of risk dynamics. Findings of our studies will be used to support decision makers and involve affected communities, fostering resilience, through our pilot case studies and our sectoral representatives.

6 Data and ethics statement

The information in the deliverable respects the principles set out in the MYRIAD-EU Ethics Plan and in the Data Management Plan.

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