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# Multi-hazard and risk informed system for Enhanced local and regional Disaster risk management

# MEDiate

## Deliverable D2.3

## A diagnosis and assessment of the primary types of cascading impacts related to European areas

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# GLOSSARY

| Acronym | Description |
|---|---|
| CI | Critical Infrastructures |
| CISI | Critical Infrastructure Spatial Index |
| DSS | Decision Support System |
| GDP | Gross Domestic Product |
| IRDR | Integrated Research on Disaster Risk |
| ML | Machine Learning |
| OSM | OpenStreetMap |

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# 1 INTRODUCTION

## 1.1 Objectives

Task 2.3 aims to assess the cascading impacts resulting from multi-hazard interactions across Europe. These cascading impacts are crucial to understand the potential to trigger, from a given hazard event, a chain reaction of consequences affecting various sectoral assets, infrastructure systems (such as transportation, energy, and water), networks, and supply chains. Key focus areas include hydrological, meteorological, and climatological hazards, with consideration to geophysical hazards.

To comprehensively evaluate the cascading impacts it is crucial to follow a methodological process that allows for the thorough identification and understanding of both direct and indirect impacts. In pursuit of this goal, Task 2.3 employs a machine learning approach, primarily based on historical data (e.g., EM-DAT and DesInventar). This approach allows us to understand the spatial and temporal evolution of multi-hazard and multi-sectoral cascading impacts. By using historical data, we identify and anticipate potential 'knock-on' effects and their evolution, providing valuable insights into the dynamics of cascading impacts in European areas. We are aware of and witness the changing climate and associated hazards globally, but despite recent advances in understanding, modelling and forecasting natural hazards (e.g. extreme winds, intense rain and geophysical events) and how they impact communities, infrastructures and livelihoods, such events can still cause high economic, environmental and human losses.

A comprehensive perspective on this issue requires acknowledging these risks in their entirety, considering hydrological, meteorological, climatological hazards and geophysical hazards, and including their interdependence in terms of impacts. Concrete examples in Europe include the July 2021 floods in Germany, the Netherlands, Luxembourg, and Belgium, along with extreme rainfall in Italy and wildfires in Southern Italy and Turkey. These events led to flash floods, landslides, airport closures, loss of lives, significant economic losses, and damage to cultural heritage. Also, examples from the MEDiate project's testbeds, like the recent heavy rain-landslide event in Iceland in December 2020, highlight the point. This event not only disrupted local infrastructure but critically blocked roads. Understanding the need to consider these cascading impacts, this deliverable delves into their interconnected consequences, recognizing the urgency of addressing and mitigating these complex challenges.

Ultimately, the results of Task 2.3 will be instrumental in enhancing our overall understanding of the interplay between different hazards and their far-reaching consequences, contributing to more informed and effective risk assessments and decision-making processes. This, in turn, will play a critical role in achieving the project's broader objectives and in facilitating the development of the multi-hazard disaster risk Decision Support System (DSS) within the framework of WPs 3, 4, and 5. By focusing on the assessment of cascading impacts and their spatial and temporal evolution, we aim to create a foundation for more comprehensive and informed risk-based assessments and decision-making that is driven by the needs of end-users and takes into account sectoral impacts.

The specific objectives of Task 2.3 are:

1. *Review and identify cascading impacts*: Examine and identify cascading impacts from past events in testbeds,
2. *Develop a framework*: Develop an impact assessment framework and demonstrate its application through a specific case study. Enhance understanding of cascading impacts by applying machine learning to analyse historical data.
3. *Sectoral impact analysis:* Analyse impacts on critical sectors, such as transportation, energy, and water. Integrate sector-specific impacts into the overall assessment,
4. Contribute to informed decision-making and support the development of a multi-hazard disaster risk DSS.

## 1.2 Scope of this report

The scope of Task 2.3 focuses on the hazard to exposure interactions and on the type of impact interaction within Work Package 2 (WP2), which is to generate critical new methods, evidence, and knowledge relating to multi-hazard interactions and cascading impacts in the European context. Starting from the areas of spatial and temporal overlap of hazards identified in T2.2, different types of impact interactions are generated in specific areas of the domain. The impact assessment is the "areal or spatial extent of the hazard" (De Angeli et al., 2022). In particular, the spatial extent of the hazard directly influences the spatial scale of the direct impacts, which can range from municipal to intercontinental levels. In some cases, even a very localized hazard can generate indirect consequences at a much larger scale (De Angeli et al., 2022).

As a part of WP2, Task 2.3 interconnected with Task 2.1 and Task 2.2: adopting the outcome of Task 2.1 and incorporating the scope of multi-hazard pairs for each testbed to deliver primary cascading impact assessment. The result of Task 2.3 will then feed into Task 2.4 and other WPs across the MEDiate project to develop DSS. The objective is to ensure coherence among the obtained results, avoiding undesirable overlaps. This linkage is crucial to ensure that each aspect of task 2.3 integrates synergistically, maximizing the overall effectiveness of our activities.

In summary, the approach of MEDiate involves the creation of a flexible multi-hazard framework (T2.1) and the primary-interacting hazards assessment in Europe (hydrological, meteorological, climatological, and geophysical) (T2.2), with a particular focus on linking various tasks to ensure a harmonious workflow and optimal results within the context of WP3.

## 1.3 Background

The impact of climate change is becoming increasingly evident and alarming, with effects extending far beyond variations in temperature and atmospheric changes. These impacts are reflected in natural hazard occurrences, illustrating the pervasive nature of climate-related challenges. As per the World Bank's assessment of primary natural hazard hotspots, around 3.8 million square kilometres and 790 million individuals globally are significantly exposed to at least two hazards (Dilley et al., 2005). Moreover, approximately 0.5 million square kilometres and 105 million people face exposure to three or more hazards. The impact of climate change is anticipated to heighten the vulnerability to multiple risks, influencing the scale, frequency, and geographic distribution of hazardous and disastrous events (IPCC, 2021).

The World Economic Forum, in its 2018 Global Risks Report, identified climate change as a central factor in global risks, highlighting extreme weather events, natural disasters, and challenges in climate change mitigation and adaptation among the top five concerns (World Economic Forum, 2018). These risks are interconnected and cascade across various domains, contributing to systemic challenges marked by increased uncertainty, instability, and fragility over the past year.

As climate change is projected to significantly alter the magnitude, frequency, return periods, and spatial distribution of climate and natural variables (Gallina et al., 2016; Peduzzi, 2019), the need to incorporate climate variability into future decision-making is escalating. This is crucial for optimizing environmental, social, and financial outcomes in the face of changing climatic conditions. Few methodologies currently incorporate climate change scenarios into assessments of future environmental risks and natural hazards.

Adopting a multi-risk perspective in climate change impact assessment can help reduce the risk of adaptation efforts aimed at one specific hazard inadvertently increasing vulnerability or exposure to other hazards. Despite the importance of this approach, integrating climate change scenarios into multi-risk assessments poses several challenges, such as determining the scale of analysis, addressing uncertainty in input data, and aggregating variables.

In this context, the necessity of embracing a multi-risk approach for evaluating the impacts of climate change is stressed by international organizations (Dilley et al., 2005; IPCC, 2012) across different spatial levels, including the European scale (EC, 2010). The IPCC's special report on extreme events and disasters (2012) underscores the importance of a multi-hazard strategy for more effective adaptation and mitigation measures, both in the present and particularly in the future.

Multi-risk assessment has grown globally and at the European level in recent decades, with a surge in applications and initiatives focused on evaluating risks stemming from various natural and human-induced hazardous events (Jha et al., 2013).
The work of Gallina et al. (2016) tackles this complex analysis, robustly describing a set of issues and challenges related to climate change that need to be considered in a multi-risk assessment process, spanning key phases. Moving to exposure, the focus is on identifying at-risk elements and projecting future scenarios. Vulnerability involves identifying vulnerability factors, resilience considerations, and scenarios for evolving vulnerabilities. Multi-risk requires defining a common scale and suitable aggregation methods. Facing these challenges emphasizes early stakeholder engagement, transparent communication of uncertainties, and clear output visualization.

One of the most concerning consequences of climate change involves the amplification of cascading impacts, where alterations in a specific aspect of climate or the environment trigger a series of reactions that propagate in multiple directions, intensifying overall impacts. This phenomenon of "cascading impacts" is a key focus in the current climate change discourse, as it highlights how an initial change can lead to a series of unexpected and sometimes devastating consequences across various sectors, from the environment to society. The intensification of cascading impacts in the context of climate change is due to intricate interdependencies, heightened vulnerability and exposure, disruption of ecosystems, social and economic inequalities, and interwoven infrastructure dependencies (IPCC, 2021). As highlighted in the IPCC Sixth Assessment Report, recognizing the amplification of cascading impacts, where alterations in one aspect prompt a chain reaction with far-reaching consequences, underscores the necessity for a holistic evaluation.

This report delivers identification and assessment of the primary types of cascading impacts in European areas as part of WP2 for the MEDiate project.

# 2 KEY CONCEPTS AND DEFINITIONS

In this report, we adopt and share key terms across the work packages (WPs) as shown in Table 2.1. We keep cascading impacts and knock-on effects distinct because cascading impacts primarily focus on the sequence of events triggered by a hazard event, emphasizing the progression within human sub-systems and the physical, social, or economic disruption caused. On the other hand, knock-on effects highlight the broader repercussions that extend beyond sectoral assets and infrastructure, emphasizing the intricate networks and supply chains' interdependencies. Separating these concepts allows for a more nuanced examination of the diverse manifestations and implications of cascading events in both specific sectors and the overall risk landscape.

Table 2.1: List of definitions related to cascading impacts

| | |
|---|---|
| **Cascade Order** | The number of stages in a propagation from a directly impacted system to an indirectly impacted one |
| **Cascading Hazard** | Cascading hazard processes refer to an initial hazard followed by a chain of interrelated hazards (e.g. earthquake triggering landslide, landslide triggering flooding, flooding triggering further landslides) |
| **Cascading Impacts** | Cascading impacts are those in which the impact of a physical event or the development of an initial technological or human failure generates a sequence of events in human subsystems that results in physical, social or economic disruption. Thus, an initial impact can trigger other phenomena that lead to consequences with significant magnitudes |
| **Conditions** | Circumstances that enable, prevent, aggravate, or mitigate dependencies and impacts |
| **Critical Infrastructure:** | An infrastructure that encompasses vital systems and assets essential for a society's functionality and national well-being |
| **Dependency Type** | Two types include geographic (systems in one region) and logical (state changes without other dependencies) |
| **Dependency** | Mechanism whereby a state change in one system can affect another |
| **Dependent System** | A system negatively affected by a failure in another system |
| **Event** | Something that occurs or takes place, such as the occurrence of a hazard |
| **Hazard** | A process, phenomenon or human activity that may cause loss of life, injury or other health impacts, property damage, social and economic disruption or environmental degradation. |
| **Knock-on effect** | Cascading repercussions across interconnected systems |
| **Impact** | The total effect, including negative effects (e.g. economic losses) and positive effects (e.g. economic gains), of a hazardous event or a disaster. The term includes economic, human and environmental impacts, and may include death, injuries, disease and other negative effects on human physical, mental and social well-being |
| **Impacted System** | A system negatively affected by an initiating event or originating system |
| **Initiating Event** | The first in a sequence of natural events affecting one or more systems |
| **Interdependency** | Mutual dependency between two systems |
| **Multi-hazard** | 1) The selection of multiple major hazards that the country faces, and<br>2) the specific contexts where hazardous events may occur simultaneously, cascadingly [sic] or cumulatively over time, and taking into account the potential interrelated effects |
| **Multi-Layer Single Hazards** | More than one hazards are considered, but not the interrelationships between these (i.e. they are treated as discrete and independent) |
| **Multi-Sectoral Cascading Impacts** | A failure in one sector causes a failure in another due to interdependencies |

| | |
|---|---|
| **Narrative** | The collection of systems affected by a specific initiating event, indicating interdependencies and the time at which they take effect |
| **Natural Hazards** | Hazards that are predominantly associated with natural processes and phenomena (caused either by rapid or slow onset events) |
| **Originating System** | A system from which a failure propagates to another system |
| **System** | A distinct unit affected by, and/or giving rise to, consequences in another unit |
| **Time Span** | The time between the start of an incident and before cascading effects occur |

## 2.1 Critical Infrastructure

The term "critical infrastructure" at its broadest level involves elements vital to societal operation (Alexander 2013b). CI consists of complex, geographically dispersed, nonlinear networks interacting with human owners, operators, and users (Amin 2002). In strategic sectors like energy, telecommunication, and transportation, developments in one part of the network can rapidly create broader effects by cascading throughout the network and potentially spilling over into others (Amin 2002: 67). These CI serve as the bedrock supporting the functioning of nations, facilitating the efficient movement of goods and people, delivering essential public services, and sustaining industrial operations. However, in a world characterized by complexity, uncertainty, and an array of potential threats, the resilience and integrity of these infrastructures face perennial challenges.
The understanding of what the CI is can differ in various countries. While infrastructures like energy, water supply, transport, etc. are understood to be critical in all countries; some others can be considered critical only in some states, (e.g. monuments of national significance). Different countries have slightly different lists detailing their critical infrastructure systems (CISs), but most contain the following systems: telecommunications, electric power systems, natural gas and oil, banking and finance, transportation, water supply systems, government services, and emergency services.
In Europe, the Council Directive 2008/114/EC establishes a procedure for designating CI in the energy and transportation sectors, aiming to mitigate significant cross-border impacts resulting from the damage or destruction of such infrastructures (Appendix - Table A.1). However, an assessment conducted in 2019 revealed the inadequacy of protection measures focused on individual structures, considering the increasing interconnection of operations related to CI. Therefore, there is a need for a new approach that takes greater account of risks, clearly defines the roles and responsibilities of critical entities, and adopts Union standards to enhance the resilience of such entities. The new approach, introduced by the 2022 directive, aims to overcome the limitations of Directive 2008/114/EC, considering the increasingly interconnected and cross-border context of operations in CI. The revised directive introduces significant changes, such as the requirement for Member States to ensure that critical entities conduct more comprehensive risk assessments (Article 12). These assessments must consider a wide range of risks, including natural and human-origin, intersectoral, and cross-border risks, providing a more holistic view of potential impacts on essential services. Additionally, the directive emphasizes that critical entities adopt technical, security, and organizational measures for resilience (Article 13), extending beyond incident prevention to include the capacity to withstand, mitigate consequences, and restore operations. The update also focuses on clarifying the roles and responsibilities of critical entities, particularly as essential service providers for the internal market, promoting a clearer definition of responsibilities and greater consistency in actions. The ultimate goal is to ensure that CI can adopt preventive, protective, and crisis management measures in an integrated manner, improving their overall ability to adapt and restore operations following potential disruptions.

The hierarchical structure of a critical infrastructure system comprises three levels, constituting a vertical classification (Rehak, 2016):

- Sector level,
- Sub-sector level, and
- Element level.

At the sector level, critical infrastructures are classified based on their functions. The sub-sector level further categorizes specific sectors and their interconnections. For instance, the transportation sector encompasses five subsectors: air, rail, water, road, and public transport. The element level consists of individual components that serve as the fundamental building blocks of the critical infrastructure sector. These elements vary in significance within the sector, depending on the potential impact their disruption or failure may generate. Figure 2.1: highlights the knock-on effects inherent in the critical infrastructure system.

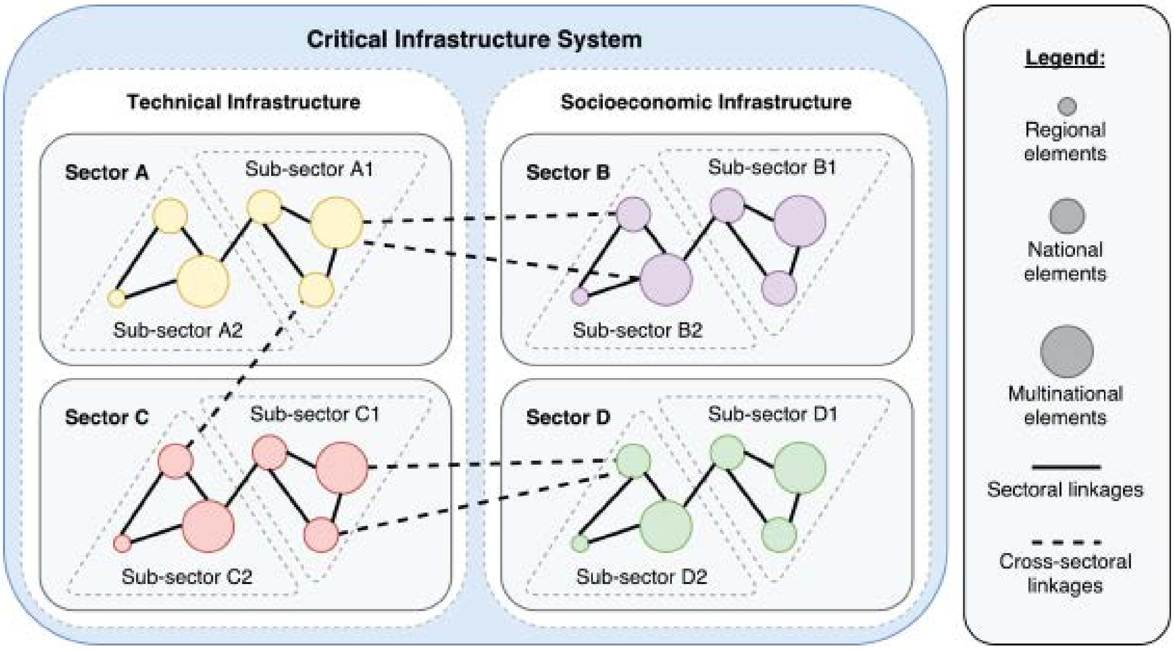



Figure 2.1: Hierarchic arrangement in a CI system (Rehak, 2016)

This level comprises two areas, namely the technical infrastructure and the socioeconomic infrastructure. The technical infrastructure includes sectors producing and providing specific commodities (e.g., energy and water supply) or sectors providing technical services (e.g., transport or ICT systems). The socioeconomic infrastructure is composed of sectors that provide social or economic services (e.g., health care, financial and currency markets, emergency services, and public administration), (Rehak, 2016).
It is imperative that a critical infrastructure system be viewed in a comprehensive manner, taking into account its networked arrangement where individual subsystems are interlinked via various types of linkages. These linkages, called dependencies (Rinaldi, 2001) are analysed in the following chapters.

## 2.2 Cascading impacts

Pescaroli and Alexander (2015) argue that “cascades” are characterized by unforeseen and nonlinear progressions of subsidiary events, spreading towards societal vulnerabilities and disrupting critical infrastructures (CI). Cascades, in this context, are defined as disruptive event sequences or consecutive failures linked by cause-and-effect relationships (Pescaroli and Alexander, 2016). The “cascading impact” is a focal point in disaster risk reduction, where the direct impact of hazard events generates a sequence of events in human sub-systems, resulting in physical, social, or economic disruption (Pescaroli and Alexander, 2016). 'Cascading disasters' occur when these effects progress over time, generating unexpected secondary events with greater impact. Examples include failures in physical structures and the social functions dependent on them, as well as inadequacies in disaster reduction strategies (Pescaroli and Alexander, 2016). Ignoring these interactions by following multi-layer single-hazard approaches, can distort risk management priorities, increase vulnerability, and underestimate disaster risk (Gill and Malamud, 2016). Understanding interactions and their networks is needed for modelling disaster events, monitor changes in vulnerability, and allocating resources effectively for mitigation and disaster risk reduction. Furthermore, because the prevalence of

cascading impacts is increasing due to climate change and increasing socioeconomic exposure and consecutive disaster vulnerability (de Ruiter et al., 2020).
Traditional single-hazard assessment treat hazards in isolation, while multi-hazard in literature is frequently used to indicate multiple single hazards that are analysed in parallel and finally integrated into a multi-risk analysis (Lewis 1984; Granger et al., 1999). Multi-hazard encompasses independent hazard analyses and the identification of spatial overlaps, referred to as "multi-layer single-hazard" approaches. Transitioning to true multi-hazard approaches involves hazard identification, understanding interactions, exploring spatial/temporal coincidences, and assessing dynamic vulnerability (Gill and Malamud, 2014).

The literature highlights applications considering combined effects of different hazards on elements at risk (Van Westen et al. 2002; Lacasse et al. 2008; Kappes et al. 2010; Gall et al., 2011; Kappes et al., 2012; Duncan et al., 2016; Rusk et al., 2022). Although the severe consequences of such domino sequences are well known, qualitative criteria are often proposed (Corominas et al., 2014), with limited studies focusing on quantitative risk assessment, mainly related to earthquakes (Keefer 1984; Romeo et al. 2006; Marzocchi et al., 2012; Rusk et al., 2022).

The distinction between “cascading hazard” and “cascading impact” is instrumental in facilitating a deeper comprehension of the dynamics that operate during catastrophic occurrences or critical incidents. 'Cascading hazard' conveys the propagation or amplification of threats initiated by an impending hazard or primary event, culminating in a sequence of ensuing threats. For instance, an earthquake can induce landslides, tsunamis, or fires, thus amplifying the overall risk landscape (Cutter et al 2009; Turner et al 2003, Keating et al 2011).
In contrast, cascading impact is related to the aftermath of an initial event or threat. Particularly, a cascading failure occurs when a disruption in one infrastructure causes the failure of elements in a second infrastructure, which subsequently disrupts the second infrastructure. These repercussions encompass damage inflicted upon CI, dislocation of key services, economic reverberations, human casualties, and other corollaries impacting the afflicted societies and communities.
Escalating failures occur when a disruption in one infrastructure triggers a domino effect, worsening an existing disruption or delaying recovery in a second infrastructure. Furthermore, if two or more infrastructure networks are disrupted at the same time, it is referred to as a common cause, wherein elements within each network fail because of some common cause (e.g., action of natural hazards affecting all local infrastructures). Critical infrastructure failures subsequently produce negative impacts that can propagate further not only within the critical infrastructure sector but also outside the sector.
The impacts can spread into two basic areas. The first instance involves impacts within the system where the failure of one CI sub-sector causes a failure of another sub-sector in what is known as a cascading impact (Rehak, 2018). In the second instance, the impacts exert influence outside the system, specifically, on society, producing negative effects on national interests such as security, the economy, and basic human needs (Rehak, 2006). In both of the above-mentioned cases, the impacts may be classified as direct or indirect from a structural point of view. Figure 2.2 shows the nature of impacts, in terms of action and duration.
The intensity and propagation of the impacts from CI system failures is affected by several external and internal factors of the system concerned. The nature of the impacts is characterized by the area and structure of the activity, intensity and duration of its occurrence, and the effects of its activity (Figure 2.2). Other important factors that contribute to creating these impacts’ natures are their intensity and duration. The impact intensity is not only from the extent of the sector failure that continues its effect on another CI sector; but also, from the level of their mutual link. If this link is weak, then the intensity is low and the subsequent impact on the affected sector is only of a partial character. On the other hand, if this link is strong, then the intensity is high, and the impact on the affected sector can be devastating. Duration is an important variable: this can be subdivided into the Short-, medium-, or Long-term (Rehak, 2018).
This is the reason why cascading impact assessment requires understanding the interdependency across critical infrastructure systems.

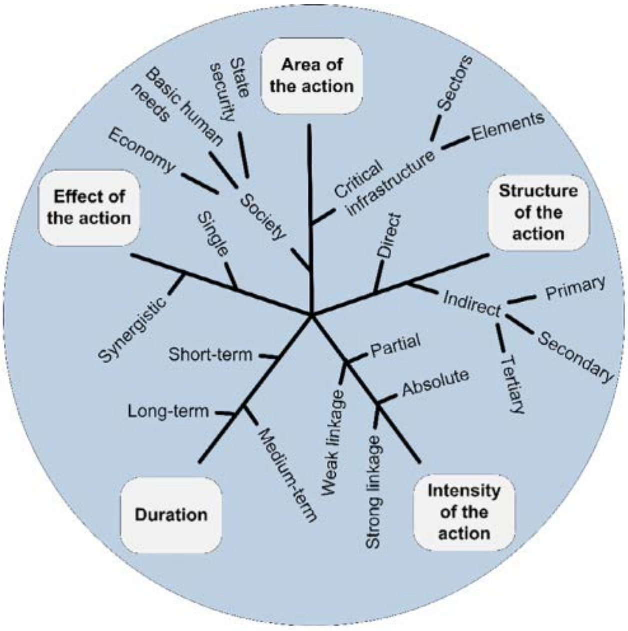



Figure 2.2: Aspects that create the nature of impacts (from Rehak, 2018)

The last useful definition to analyse Cascading Impacts on CI is the distinction between Direct Impacts, Cascading Impacts, and Synergistic Impacts (Figure 2.3):

- *Direct impacts* arise from disruptions of critical elements, causing immediate effects on society.
- *Cascading impacts* propagate through interdependent infrastructures, amplifying disruptions across sectors.
- *Synergistic impacts* result from simultaneous failures of multiple elements, magnifying their collective repercussions on society.

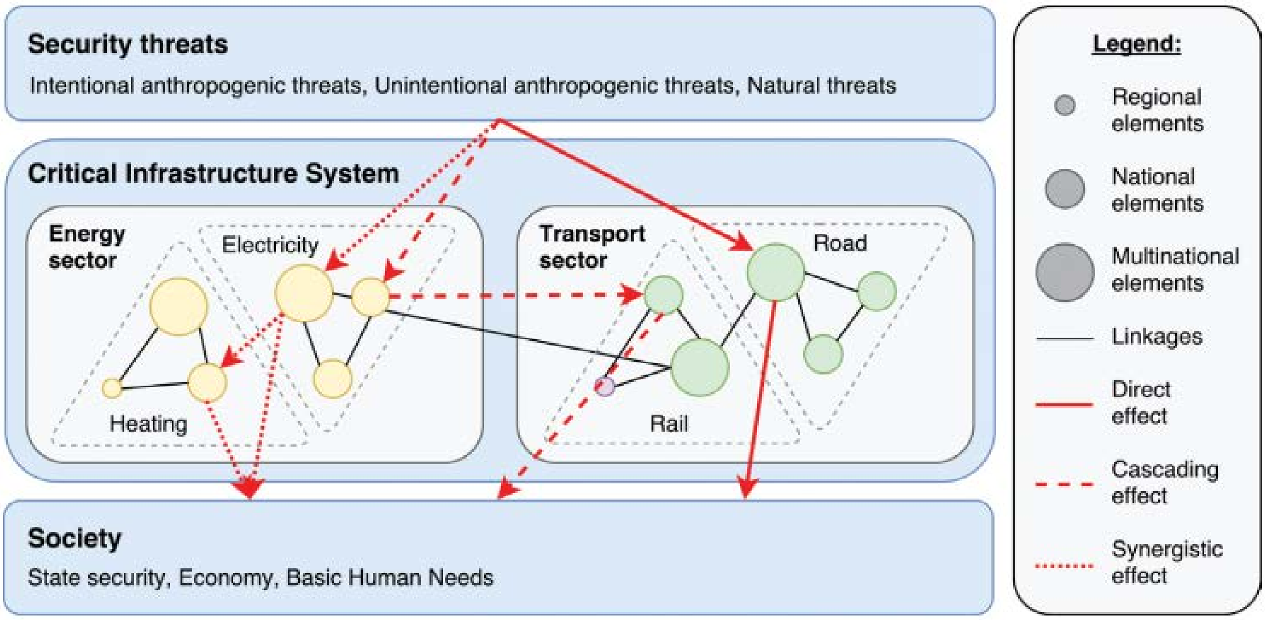



Figure 2.3: Ways of impact propagation in a critical infrastructure system (Rehak, 2016)

Cascading impacts are not constrained to a single domain and may manifest disparate impacts contingent upon the environment. Illustratively, several cascade manifestations encompass:

- *Power grid cascade:* Malfunctions within a power grid can incite a cascade effect wherein the failure of a single power station exerts additional stress on adjacent stations, thus triggering a cascading sequence of failures and widespread power outages. (e.g. the 2006 European blackout, Van der Vleuten and Lagendijk, 2010)
- *Communication cascade:* In the domain of communication networks, the malfunction or overloading of a single network node can instigate a cascade effect, eventually causing the collapse of other nodes. The consequence is network congestion and the disruption of connectivity (e.g. the 2003 Italian electrical blackout where the entire communication network was affected, Buldyrev et al., 2010)
- *Social cascade:* Social systems may witness cascade effects due to the dissemination of information or behavioural patterns. For instance, the rapid dissemination and uptake of a viral video or a social media trend can significantly influence the behaviours of individuals, leading to a cascade of imitative behaviours or alterations in social norms (e.g. the spread of the ALS Ice Bucket Challenge on social media, Pressgrove et al., 2018)
- *Environmental cascade:* Alterations within one facet of the environment can serve as the catalyst for a cascade effect across interconnected environmental components. A case in point is California, where prolonged drought (2012-2016) was followed by intense rainfall, fuelling vegetation growth. Subsequent dry conditions led to wildfires. When rain returned, debris flows occurred in Montecito in 2018, illustrating the environmental cascade's unpredictability (AghaKouchak et al., 2020).

Cascading events may be induced by diverse triggering factors and mechanisms, the specific triggers being contingent on the contextual milieu in which they manifest. Figure 2.4 delineates the factors that can inaugurate cascading effects:

- *Triggering Event*: Cascades are frequently inaugurated by an initiating event, which can range from a minor perturbation to a substantial change within a segment of the system. This event serves as the fulcrum for initiating a sequence of reactions that permeate the system, ultimately precipitating a cascade.
- *Interconnectedness*: Cascades frequently emanate from interconnected systems or networks, where actions or alterations in one component can precipitate substantial effects in others. This interconnectivity facilitates the propagation and amplification of the cascade effect.
- *Positive Feedback Loops*: Positive feedback loops hold a pivotal role in amplifying the effects of a trigger event, culminating in a cascade. Within these loops, the system's output serves to corroborate or magnify the initial perturbation, engendering a self-reinforcing cycle.
- *System Complexity*: Complex systems featuring numerous interdependent components are more susceptible to cascades. The interactions and dependencies amid diverse constituents within the system have the potential to instantiate a chain reaction, whereby modifications in one component can trigger corresponding changes in others.
- *Nonlinear Dynamics*: Cascades often find their genesis in nonlinear dynamics, wherein minor alterations can have disproportionate or unanticipated consequences on the system. Nonlinear interactions can precipitate the rapid and unpredictable escalation of cascades.
- *Threshold Effects*: Cascades may be initiated when a system crosses a critical threshold. Once this threshold is traversed, the system may undergo precipitous and irrevocable transformations, thereby ushering in a cascade effect.
- *Feedback Mechanisms*: Feedback mechanisms, encompassing delayed or amplified responses to alterations, can contribute to the occurrence and perpetuation of cascades. Positive or negative feedback loops may either intensify or ameliorate the cascade effect.

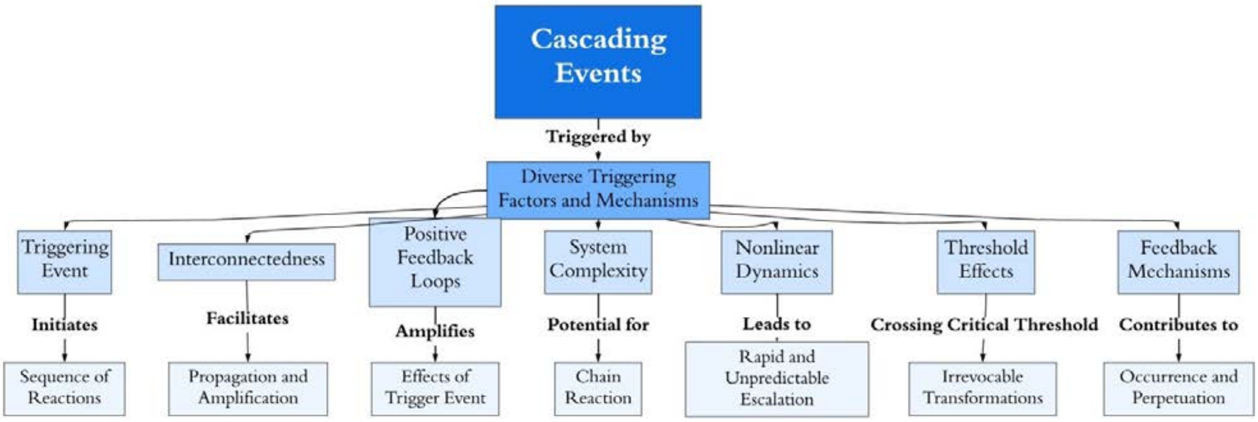



Figure 2.4: Flowchart depicting the key factors and mechanisms triggering cascading events in complex systems

## 2.3 Knock-on Effects

The definition of cascading impacts is directed towards the intricate network of sectoral assets and infrastructure. This expansive network encompasses vital domains including transportation, energy, and water supply, serves as the lifeblood of contemporary societies. It ensures the sustenance of economic prosperity, public welfare, and national security. The concept of "knock-on effects" reveals a detailed and frequently overlooked aspect of the overall risk scenario, pointing out that the idea of cascading consequences highlights a less recognized but important part of the broader risk landscape. It signifies the cascading ramifications that propagate not only through sectoral assets and infrastructure but also through the intricate networks and supply chains upon which these assets depend. It underscores the intrinsic interdependencies that have become a defining feature of our increasingly interconnected and interwoven world.
As our built environment grow ever more dependent on the intricate web of sectoral assets and infrastructure, the importance of understanding and mitigating knock-on effects is paramount. The repercussions arising from the disruption of these interconnected systems possess the potential for amplification in terms of scale and scope, transcending the boundaries of individual sectors and extending into unforeseen domains. Such knock-on effects can trigger profound challenges for policymakers, emergency responders, and the general public alike.

The terms "cascading impact" and "knock-on effect" are very similar and are often used interchangeably but they exhibit subtle differences relevant to a scientific review.

- **Cascading Impact:**
    - Emphasizes the sequential nature of the consequences.
    - Focuses on the chain reaction triggered by an initial event, where one hazard leads to another, and then another, potentially amplifying the overall impact.
    - Often used in the context of natural hazards and disaster risk management.
    - Example:
        - An earthquake triggers a landslide, which then blocks a river causing flooding downstream. This flooding damages infrastructure and disrupts livelihoods, creating a cascading series of negative impacts;
        - A volcanic eruption triggers ashfall, impacting agricultural productivity (primary impact) followed by food shortages (secondary impact) and economic decline (tertiary impact).

- **Knock-on Effect:**
  - Has a broader scope and can refer to both positive and negative consequences.
  - Highlights the indirect and secondary nature of the effects.
  - Can be used in a wider range of contexts, including economics, social issues, and technology.
  - Example:
    - A new technological innovation leads to increased productivity, which in turn boosts economic growth and creates new jobs. This is a positive knock-on effect.
    - A medical breakthrough leads to increased life expectancy (primary impact), which in turn increases demand for healthcare services (secondary impact) and potentially alters population demographics (tertiary effect).

In conclusion, both terms describe a sequence of consequences. However, "cascading impact" emphasizes the sequential and potentially amplifying nature often seen in natural hazards, while "knock-on effect" has a broader application across various scientific disciplines and can encompass both positive and negative outcomes. Task 2.3 will focus on cascading impacts.

## 2.4 Dependencies and Interdependencies

As explained, Critical Infrastructure Systems (CIs) are not discrete entities; rather, they exhibit a high degree of interconnectedness and mutual interdependence. For instance, water and telecommunication systems rely on a continuous supply of electricity to maintain their routine operations, while electric power systems necessitate access to water and diverse telecommunication services for effective power generation and distribution (Ouyang, 2013).
In the literature several definitions of “dependency” and “interdependency” are present; however the work of authors Rinaldi et al. (2001) is pivotal in evaluating the links between elements. Between various infrastructures, there can be dependencies that can spread after a disruption of the functionality of one infrastructure and its co-dependent infrastructure.
In the context of critical infrastructure dependency and interdependencies, Rinaldi (2001) defines:

- *Dependency*: A linkage or connection between two infrastructures, through which the state of one infrastructure influences or is correlated to the state of the other (Figure 1.1:). Then infrastructure A depends on infrastructure B when a variation in this latter has the capability to influence (e.g. modify) some states (e.g., behaviours, characteristics, properties, etc.) of infrastructure A. It is, therefore, a uni-directional relationship.
- *Interdependency*: A bidirectional relationship between two infrastructures through which the state of each infrastructure influences or is correlated to the state of the other. More generally, two infrastructures are interdependent when each is dependent on the other (Figure 1.1:). Hence, infrastructures A and B are interdependent if A depends on B and, at the same time, B depends on A.

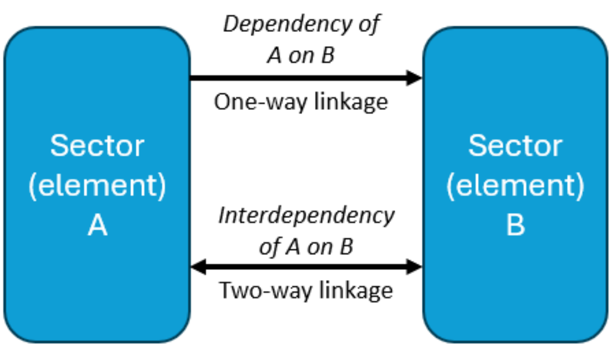



Figure 2.5: Types of linkages in a critical infrastructure system (adapted from Rehak, 2016)

Rinaldi (2001) demonstrated the interdependency of critical infrastructure elements and defined four types of links:

1. *Physical:* the type of interdependency when each of two infrastructures are dependent on the material output(s) of the other;
2. *cyber*: the type of interdependency when an infrastructure is dependent on the information transmitted through the information infrastructure;
3. *geographical:* the type of (inter)dependency when local environmental events can create state changes in all infrastructures; it occurs when elements of multiple infrastructures are in close spatial proximity;
4. *logical*: the type of (inter)dependency when the state of each of two infrastructures depends on the state of the other via control, regulatory or through a mechanism not a physical, cyber or geographic connection.

Figure 2.6 shows an example of electric power infrastructure dependencies and interdependencies.

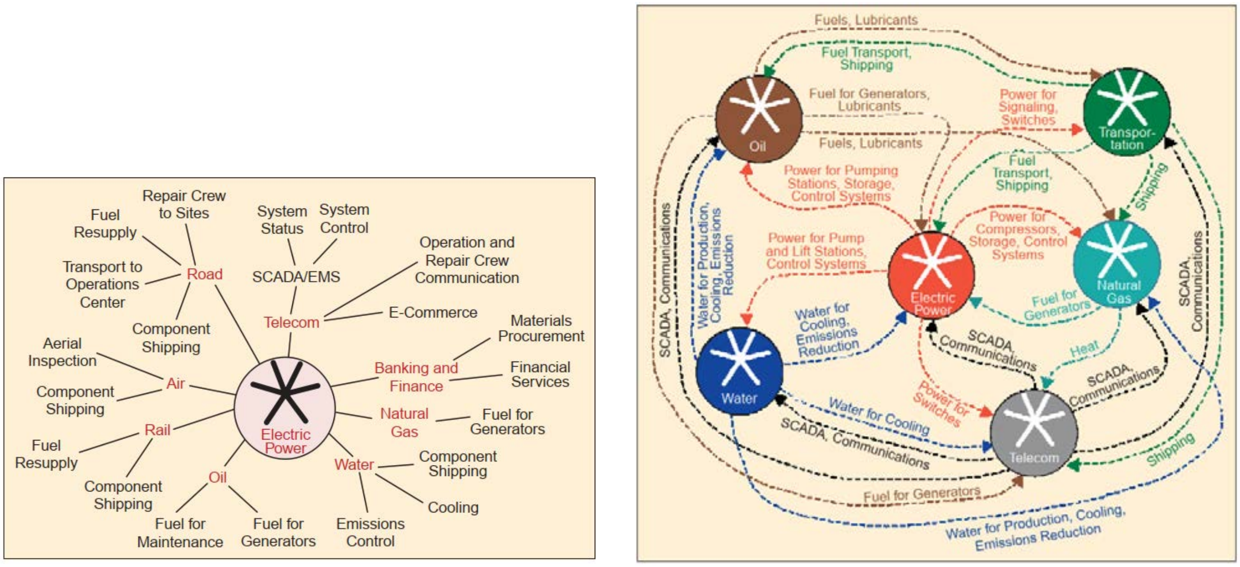



Figure 2.6: Left panel: examples of electric power infrastructure dependencies (from Rinaldi, 2001);
Right panel: Examples of electric power infrastructure interdependencies (from Rinaldi, 2001)

Another possible method of classifying links is represented by their division according to the level of the link, specifically (Rehak, 2016):

- *sectoral level*: this is the type of link represented by the dependence or influence of sectors across the entire critical infrastructure system (e.g., the dependency of the integrated rescue system on road infrastructure)
- *sub-sectoral level*: this is the type of link represented by the dependence or influence of sub-sectors within a given critical infrastructure sector (e.g., the impact of disrupted road infrastructure on rail transport)
- *element level*: this is the type of link represented by the dependence or influence of individual elements within a given sub-sector (e.g., the dependence of a motorway on a motorway bridge or the effect of motorway failure on surrounding roads).

The linkages described in Figure 2.5 are found both at the vertical level (sector-element) and the horizontal level, which includes linkages between the cause-failure-impact. These linkages occur at the following levels:

- Among the elements of a critical infrastructure's various sectors (i.e. cross-sectoral linkages).
- Among the elements within a critical infrastructure sector (i.e. sectoral linkages).
- Among a critical infrastructure's elements and the society.

Modelling the anticipated propagation of impacts constitutes an important approach contributing to their minimization in a critical infrastructure system. However, it involves a complex process which should be based on mathematical modelling as well as on the integration of innovative approaches to analyse the critical infrastructure system.
Without prediction modelling tools, it would be impossible to identify the potential impacts of disruptions to or the failures of a CI over time, considering all the types of linkages discussed above exist in a critical infrastructure sector at both the vertical and horizontal levels.

# 3 REVIEW OF METHODS TO ASSESS CASCADING IMPACTS

This section reviews approaches and methodologies in evaluating impacts across critical systems, aiming to uncover insights, best practices, and challenges in the field.
We start the review understanding the interplay between various hazards and analysing cascading hazards. Once the review of cascading hazards is concluded, aiding in identifying potential chains of events and assessing potential overall consequences, the review proceeds with analyses of cascading impacts, focusing on the effects of such event chains and the impacts that may result in critical infrastructure.

## 3.2 Hazards and related cascading impacts

The following paragraphs briefly address hydrogeological, meteorological, and geophysical hazards covered in MEDiate. This section also helps focus on another relevant issue in multi-hazard approaches, namely the scale of interest, which influences how interactions are characterized. Approaches may be event-based or probabilistic, with both offering benefits in different contexts. For global relevance, probabilistic viewpoints generalize interactions, while regional and local contexts necessitate specific populations of individual events. Temporal considerations, such as forecasting time windows and resolution, also distinguish globally relevant and location-specific multi-hazard approaches (Selva, 2013; Chang et al., 2018; Zscheischler et al., 2018). Additionally, consecutive disasters can occur at different spatial and temporal ranges, ranging from days to months and years apart, depending on the recovery rate. Indeed, disasters, as highlighted in de Ruiter et al. (2020), occur when a hazard coincides with exposure and vulnerability. All these risk components are dynamic (UNDRR, 2016), with the potential to increase or decrease in response to the occurrence of a previous hazard or disaster (Peduzzi, 2019).
Below are the cascading impacts in various multi-hazard frameworks.

### 3.1.1 Cascading Impacts related to Hydrological hazards

In MEDiate, three main hydrological hazards are addressed: floods, landslides, and storm surges.
Floods are the most common natural hazards in the world (Kundzewicz et al. 2014), affecting more than two billion people globally between 1998 and 2017 (Wallemacq & House 2018). During this period, 3,148 reported flooding incidents caused USD 656 billion in economic damages and killed more than 142,000 people worldwide (Wallemacq & House 2018). Several studies have shown that flood damages have been increasing over the past 60 years (Downton et al. 2005, Kundzewicz et al. 2018) and attributed this to changes in climate and human settlement and activities in flood-prone regions (Dottori et al. 2018).
In the context of multi-hazard interactions, as discussed earlier, cascading events exhibit significant variation in spatial and temporal scales, primarily impacting the local scale within short durations. These local-scale occurrences, however, are intricately connected to larger-scale systems influenced by planetary-scale factors such as shifts in radiation balance, mean temperature, sea level, and the jet stream (Zscheischler et al., 2018). The non-stationary nature of cascading impacts is clearly illustrated by floods, a result of both anthropogenic climate change and localized alterations due to urbanization (Zscheischler et al., 2018; Blöschl et al., 2007; Vorogushyn et al., 2018).

Existing studies offer well-established methods to determine exposure to floods (Lyu et al., 2018) and direct flood impacts (Winter et al., 2016; Kellermann et al., 2016). Even though indirect impacts and cascade effects are widely assumed to be more significant due to the interconnected nature of networks (Gil and Steinbach, 2008; Pant et al., 2018; Arrighi et al., 2017), few works are available which address indirect impacts and cascade effects in time and space (Pant et al., 2018; Arrighi et al., 2017).
Among these works, indirect impacts and cascade effects are mostly addressed with complex conceptual frameworks that, for their application, would require a significant number of models and data (Fekete, 2019; Emanuelsson et al., 2014), simplified risk indexes (Lyu et al., 2018; Balijepalli and Oppong, 2014; Singh et al., 2018) and/or very limited application to real-world case studies (Arrighi et al., 2019; Pant et al., 2018).

A robust and widely recognized methodology for assessing multi-hazard impacts, particularly in the context of floods, is the approach proposed by Arrighi et al., 2021. This methodology employs hydraulic simulations to evaluate the effects of flooding on water networks, encompassing the modelling of network breaches and the assessment of local pressures at water network nodes. Additionally, the methodology considers the impact on the road network, evaluating the reduction in traffic speed due to flooding. The depth of water on roads determines closures and reduced vehicle speeds. Furthermore, it addresses the accessibility of critical nodes in the water network, such as pumping stations. The lack of accessibility to these critical nodes can impact repair and replacement activities, influencing the post-event recovery time. The concept of post-event recovery time is emphasized as a key metric for resilience, representing the duration required to return to normal conditions following a significant event.

The method proposed by De Angeli et al. (2018) utilizes the impact assessment model INDRA (Viavattene et al., 2018) to assess the impacts of coastal and fluvial flooding events. Considered indicators encompass risk to human life, household displacement, financial impacts on residences and businesses, as well as disruptions in business and transportation sectors. The model evaluates both direct and indirect impacts, relying on vulnerability indicators and damage thresholds related to water depth and velocity.
Beyond the chosen assessment method, flooding-related cascading impacts may compromise critical infrastructure, such as roads and bridges, due to soil erosion and water force. Water supply contamination is another cascading effect, affecting public health and straining healthcare systems. Floods can trigger emergency evacuations, impacting connected resources and logistics, further influencing emergency response capacity. Economically, floods can result in significant losses for local and national businesses, affecting the workforce and production.

The work of Van Westen (2005) represents a milestone in assessing landslide hazards by considering various types of landslides with their specific characteristics and causal factors. It acknowledges their potential co-occurrence with other hazards, such as floods or earthquakes. After collecting data, the methodology conducts a susceptibility assessment using diverse methods, including inventory-based, heuristic, statistical, or deterministic approaches. Exposure analysis and vulnerability assessment utilize a combination of expert opinions, empirical data, and physically based analytical or numerical models to define vulnerability classes. The outlined methodology integrates hazard, vulnerability and exposure through calculation of various scenarios, considering landslide type, volume, triggering event return period, and type of element at risk. This results in both quantitative risk assessment, expressed through risk curves plotting expected losses against the probability of occurrence for each landslide type (uncertainty is considered based on input uncertainties), and qualitative risk assessment, through spatial multi-criteria evaluation, integrating hazard and vulnerability indices.
Hazard assessment for multiple landslide sources depends on the scenario: for multiple types of landslides is done independently for each landslide type, merging results at the risk level; composite landslides may involve joint probability approaches; complex landslides can be addressed using event trees or Bayesian event trees; multiple interacting scenarios scenario requires distributed use of ETs or BETs, or a single ET/BET, depending on the scale and selected hazard descriptors (Corominas et al., 2014).
Integrating the understanding of landslides with the assessment of cascading impacts allows for a comprehensive perspective on the complexity of risks. Specifically, a landslide can serve as the starting point

for additional impacts, such as flooding due to debris accumulation or the compromise of critical infrastructure. Other examples of cascading impacts related to landslides include disruption of transportation networks, leading to increased emergency response times and hampering the evacuation of affected areas. Additionally, landslides may trigger soil erosion, impacting water quality and posing further challenges to critical infrastructure, such as water supply systems. The cascading impacts can extend into social and economic realms, affecting communities, businesses, and overall regional resilience.

Storm surges related cascading impacts share similarities with those related to floods, as both involve the rise of water levels. However, the specific impacts may vary depending on the unique characteristics and dynamics of storm surges compared to river floods. Both can cause coastal erosion, flooding of low-lying areas, and damage to critical infrastructure, but storm surges are specifically associated with coastal areas and may entail additional risks such as sea level rise and storm surge waves.

### 3.1.2 Cascading Impacts related to Meteorological hazards

In MEDiate project, two main meteorological hazards will be addressed: extreme precipitations, and extreme heat and droughts. Precipitation extremes do not have a universal definition; therefore, several definitions and indices have been formulated. For example, some indices proposed by the Expert Team on Climate Change Detection and Indices (https://www.climdex.org/) consider the monthly maximum 1-day precipitation, daily precipitation larger than 10 or 20 mm, and so on. In hydroclimatology, analyses on extreme precipitation typically deal with annual maxima or peaks over threshold (see Katz et al. 2002, Papalexiou et al. 2018, Westra et al. 2012).

Precipitation extremes impact ecosystems and societies in many ways. For example, extremes cause waterborne disease outbreaks, stress sewage networks, trigger landslides, wreck homes and buildings, damage crops and affect agricultural production, impact traffic conditions, and—most importantly—lead to heavy and deadly flooding.

Understanding potential cascading impacts before, during, and after extreme precipitation events is crucial for mitigating impacts. Adequate knowledge of event cascades, critical infrastructure, and vulnerable elements is key. Long-term management also requires awareness of potential cascading effects in the months to years following an event, taking into account the predictability of these events. To address forecasting challenges, a robust approach was developed by the EU-funded H2020 ANYWHERE innovation project aims to develop a Multi-Hazard Early Warning System. The system proposed by Lawrence et al. (2020) integrates advanced algorithms with unconventional data sources like radar, satellite imagery, and social media to enhance predictive capabilities during dangerous events. Forecasts for severe events, especially in the medium range, pose challenges, requiring mitigation actions based on factors such as lead time, occurrence probability, and projected severity. Beyond the chosen assessment method, the main cascading impacts related to extreme precipitation are: i) flooding and infrastructure damage due to flash floods and river overflow, compromising critical infrastructure like roads, bridges, and buildings, ii) and landslides due to soil saturation.

Regarding extreme heat, we know that high temperature, intensified by global warming, can dry out the soil, increasing plant stress and water use (Dai et al. 1999, Flanagan & Johnson 2005). Heat waves not only strains the electric grid due to higher energy demand but is further exacerbated by urbanization, where structures radiate heat, leading to increased energy consumption and greenhouse gas emissions (Rizwan et al. 2008). Droughts are also a consequence. Defining drought is challenging, given various indices reflecting different aspects of water availability (Dracup et al. 1980, Gumbel 1963, IPCC 2012, Palmer 1965, Van Loon et al. 2016). As the impacts of climate change become clearer, recent research focuses on understanding droughts in a warming world (IPCC 2012, 2013). Changes in precipitation and snow cover, along with predictions of global precipitation redistribution, have implications for regions sensitive to soil moisture changes (IPCC 2013, Seneviratne et al. 2006, Trenberth 2011). Hypothesized drought-heat interactions involve surface energy partitioning, affecting heat flux, surface net radiation, changes in solar radiation, precipitation-mediated feedbacks, and broader impacts on atmospheric circulations (Seneviratne et al., 2010).

The main cascading impacts of extreme heat include: i) heat-related illnesses, ii) straining healthcare systems, and iii) an increased demand for cooling, leading to power outages from overloaded grids. Extended high temperatures exacerbate drought conditions, intensifying water loss, disrupting ecosystems, reducing crop yields, compromising water quality, and contributing to societal challenges such as poverty, migration, and social unrest.

### 3.1.3 Cascading Impacts related to Geophysical hazards

Earthquakes have a global relevance, as understanding their implications is crucial for addressing the security and resilience challenges in critical infrastructures considered by the project. According to the Munich RE 2023 report, earthquakes are identified as the most economically destructive disasters. This is evident in the ranking of overall losses in Europe of this year, where the earthquake in February 2023 in Turkey and Syria holds the top position. Indeed, the risk is particularly pronounced in densely populated and heavily constructed urban areas, such as Istanbul and Izmir in Turkey, Catania and Naples in Italy, Bucharest in Romania, and Athens in Greece. MEDiate project aims to address the cascading impacts of earthquakes, considering their widespread impact and the vulnerability of key urban centres. The study by Daniell et al. (2017) highlights the historical impact of earthquakes, attributing fatalities and economic losses not only to the seismic events but also to secondary consequences such as fires, tsunamis, and landslides. It reveals that a substantial portion of fatalities and economic losses, specifically 40%, is associated with the cascading impacts triggered by earthquakes.

Many studies have highlighted the significant triggering component of secondary disasters stemming from earthquakes. Fan et al.'s (2019) review comprehensively addresses the numerous cascading impacts that ensue. While it is true that immediately after the event, the seismic shaking induced by earthquakes is recognized as a trigger for various landslide types, ranging from small soil failures to large rock avalanches, numerous other secondary and subsequent events need to be considered. The study emphasizes the importance of understanding post-seismic processes, such as river systems affected by coseismic landslide debris and the heightened susceptibility to rain-induced landslides in the aftermath of earthquakes. Fan et al. (2019) propose also improved tools for earthquake-induced hazard and risk assessments, recognizing the cascade of surface processes and their immediate as well as protracted consequences. Additionally, it delves into the sediment cascade, investigating the mobility and eventual settling of sediments over time, offering insights into paleo seismic research and the geologic evolution of mountain landscapes shaped by multiple earthquake cycles. Meyer et al. (2006) focus on seismic-induced liquefaction features and active strike-slip faults in Bhutan, trying to quantitative assess the potential cascading impacts, particularly in the form of landslides, avalanches, and glacial hazards.

Tang et al. (2019) propose a robust framework for addressing cascading effects of earthquakes in urban areas. It includes the determination of a space and time window for analysis, the development of cascading effects scenarios, and the analysis of the cascading effects scenario network. The method employs a disaster chains analysis to identify hazardous event transitions and assesses damages caused by secondary events. Furthermore, it utilizes network analysis indicators to measure the characteristics of the cascading effects scenario network, such as degree centrality, betweenness centrality, and network density. Overall, this method aligns with the Event Tree approach, specifically incorporating elements of Event Tree and Bayesian Event Tree methodologies. Wang et al (2013) also built earthquake disaster chains by applying Bayesian networks to evaluate the probability of induced hazardous events.

Overall, the comprehensive analysis underscores the need for a holistic approach to earthquake risk appraisal that considers both the immediate and long-term impacts of seismic events on landscapes, especially considering the numerous cascading impacts that earthquakes can trigger.

The main cascading impacts related to earthquakes and affecting infrastructures include structural damage to buildings and bridges, disruptions to transportation networks, such as roads and railways, potential liquefaction of soil leading to further instability, and the risk of secondary events like tsunamis or landslides. These impacts can result in a domino effect, affecting critical infrastructure and causing widespread consequences for communities and economies.

## 3.2 Assessing Cascading-impacts

Once the probability of multiple hazard sources has been assessed, there are existing approaches to calculate cascading impacts. Two recognized and valid methods are outlined below, both addressing multi-hazard impact assessment but differing in approach and methodology details.
This section reviews the studies in the field and broadly groups the existing modelling and simulation approaches into six types (Ouyan, 2013):

1. *Empirical approaches*: these methods analyse historical incident data and expert experiences to identify failure patterns and vulnerabilities (Chou and Tseng, 2010; Franchina et al., 2011; Mendoca and William, 2006),
2. *Agent-Based approaches*: agent-based models consider infrastructure as complex adaptive systems, incorporating dynamic feedback loops (Basu et al., 1998; North, 2001a; North, 2001b; Thomas et al., 2003),
3. *System Dynamics-Based approaches*: they use causal-loop diagrams and stock-and-flow diagrams to study feedback loops within CI systems (Brown et al., 2004; Bush et al., 2005),
4. *Economic Theory-Based approaches*: these focus on economic interdependencies within CI systems, including input-output methods and general equilibrium theories (Haimes et al., 2008; Rose, 2005; Rose and Liao, 2005),
5. *Network-Based approaches*: CI systems are represented as networks, either topologically or by analysing dynamic flow processes (Albert et al., 2000; Buldyrev et al., 2010; Hines et al., 2010),
6. *Other approaches*: various statistical and dynamical modelling approaches exist, incorporating techniques from machine learning or systems theory (Beccuti et al., 2012).

The following tables (Table 3.1, 3.2, 3.4, 3.5) summarise the main characteristics of each approach.

Table 3.1: Empirical Approaches overview

| Feature | Description | Strengths | Weaknesses |
|---|---|---|---|
| **Data Collection** | Relies on historical data from various sources:<br>• Incident reports<br>• News media<br>• Expert assessments | Provides insights into real-world events. | • Underreporting of failures can skew results.<br>• Lack of standardized data collection methods limits comparability. |
| **Analysis Methods** | Analyses historical data and expert knowledge to understand CIS interdependencies. | • Identifies frequent and significant failure patterns.<br>• Quantifies interdependency strength<br>• Analyses time-series data to reveal operational and logistical interdependencies.<br>• Conducts surveys to assess resilience factors under disruptions. | • Relies on historical data, limiting prediction for entirely new scenarios.<br>• Limited data can lead to inaccurate analysis results. |

| | | | |
|---|---|---|---|
| **Applications** | Informs decision-making for:<br>• Mitigation strategies<br>• Emergency response<br>• Risk analysis | • Provides data for identifying vulnerabilities of CIS.<br>• Offers input and validation for other modelling approaches. | |
| **Future Potential** | Integration with statistical learning theory for:<br>• Improved risk management<br>• Drawing insights from large, complex datasets. | | |

Table 3.2: Agent-based Approaches overview

| Feature | Description | Strengths | Weaknesses |
|---|---|---|---|
| Modelling Paradigm | • Bottom-up | • Captures complex behaviours and interactions between agents. | • Reliant on assumptions about agent behaviours (difficult to justify). |
| Agent Representation | CI components as autonomous agents with decision-making capabilities. | • Enables scenario-based analysis (what-if simulations). | • Difficulty in calibrating simulation parameters due to lack of data. |
| Analysis Capabilities | • All types of interdependencies | • Integrates with other modelling techniques for a more comprehensive analysis. | • Existing models often focus on specific aspects (e.g., market structures). |

Table 3.3: System Dynamics-Based Approaches overview

| Feature | Description | Strengths | Weaknesses |
|---|---|---|---|
| **Modelling Paradigm** | • Top-down | • Captures dynamic and evolutionary behaviour under disruptions. | • Semi-quantitative method relying on expert knowledge. |
| **Key Concepts** | Feedback loops, Stocks, Flows | • Analyses long-term system evolution and investment recommendations. | • Requires a large amount of data for parameter calibration (often limited). |
| **Analysis Capabilities** | • Investment recommendations | • Incorporates multi-attribute utility functions for decision support. | • Difficulty in analysing component-level dynamics (e.g., infrastructure topology changes). |
| **Validation** | • Primarily conceptual | | • Limited validation due to focus on conceptual validation. |

Table 3.4: Economic Theory-Based Approaches overview

| Feature | Description | Strengths | Weaknesses |
|---|---|---|---|
| **Sub-approaches** | 1. Input-Output (I-O)<br>2. Computable General Equilibrium (CGE) | | |
| **I-O Based Methods** | Uses Leontief I-O model to represent economic relationships between sectors. | Easy to analyse interdependencies and inoperability propagation. | • Limited to component-level analysis. |
| **I-O Strengths** | • Large-scale databases available for analysis. * Suitable for macro-economic or industry-level analysis.<br>• Easy to perform parameter sensitivity analysis. | • Interdependency matrix based on normal economic operations (may not reflect real-time situations). * Large perturbations or new disruptions can lead to significant errors. | |
| **CGE Based Methods** | • Extension of I-O models that considers consumer/producer behavior and resource constraints. | • Captures non-linear interdependencies and economic resilience. | Calibration of production/utility functions can be difficult with limited data. |
| **CGE Strengths** | • Analyses substitution possibilities for resources and services.<br>• Models different types of interdependencies in a single framework. | • Resilience analysis relies on external data for elasticity values (limited studies available). | |

Table 3.5: Network-Based Approaches overview

| Feature | Description | Strengths | Weaknesses |
|---|---|---|---|
| **Overall Approach** | • Represent CIS components as nodes and connections as links in a network. | • Provides intuitive CIS representations.<br>• Offers detailed descriptions of network topologies and flow patterns. | • Relies on network abstractions, which may not capture all real-world complexities. |
| **Sub-approaches** | | | |
| *Topology-Based Methods* | • Analyse CIS interdependencies based on network structure. | • Analyses cascading failures based on component states (functional/failed).<br>• Identifies critical components for improving robustness.<br>• Explores mitigation strategies through network modifications | • Ignores flow dynamics within and between CISs, potentially leading to inaccurate results. |

| | | | |
|---|---|---|---|
| | | | • Limited to analysing impact on network connectivity, not system performance. |
| *Analytical Methods (within Topology-Based)* | • Analyses large-scale networks with simplified assumptions. | • Offers closed-form solutions for specific network configurations and failure scenarios. | • Limited to idealized network models, may not be applicable to real-world CI with heterogeneous components. |
| *Simulation Methods (within Topology-Based)* | Analyses diverse network configurations and failure scenarios. | • Captures component heterogeneity and considers various performance metrics (e.g., lost service hours).<br>• Enables assessment of mitigation strategies under different conditions. | • Can be computationally expensive for large-scale networks with complex failure dynamics. |
| *Flow-Based Methods* | Analyse CI interdependencies by considering flow characteristics within and between systems. | • Provides more realistic modelling of CIS operations.<br>• Analyses impact of disruptions on system performance metrics (e.g., power outages, data loss).<br>• Identifies optimal restoration strategies and long-term investment needs. | • Can be computationally expensive for highly detailed models with complex flow dynamics.<br>• Requires data on specific operation mechanisms of each CI, which may not be readily available. |

## 3.3 Machine Learning techniques for cascading impact assessment

Machine learning (ML) is a subfield of artificial intelligence (AI) that focuses on the development of algorithms and statistical models that enable computers to perform tasks without explicit programming. The main goal of machine learning is to allow computers to learn from data and make predictions or decisions based on that learning. The applications of machine learning are extensive and span across various domains, playing key roles in image and speech recognition, natural language processing, fraud detection, recommendation systems, autonomous vehicles, healthcare diagnostics, and financial forecasting.

Machine learning encompasses various types, processes, algorithms, and evaluation metrics. Supervised learning involves training models on labeled data, unsupervised learning discovers patterns without labels, and reinforcement learning teaches agents through interaction. The machine learning process includes data collection, preprocessing, feature engineering, model training, evaluation, and deployment. Common algorithms include linear regression, decision trees, SVMs, and neural networks. Deep learning involves neural networks with many layers, such as CNNs (Convolutional Neural Networks) and RNNs (Recurrent Neural

Networks). Evaluation metrics include accuracy (measure of correct predictions), precision (measures how many of the predicted positive instances are actually positive), recall (measures how many of the actual positive instances are correctly predicted by the model), and F1 score (measures the balance between precision and recall. Popular tools and libraries include Python, scikit-learn, TensorFlow, PyTorch, and Jupyter Notebooks.

Several machine-learning based methods are proposed in the literature quantitatively assess cascading impacts, particularly related to CIs and to power grids. Wang et al. (2018) propose a predictive model to assess effects on critical infrastructure systems under different types of attacks. The approach involves modelling various attack scenarios, including random, malicious, shell-based local, and oriented local attacks. The study considers three types of cascading effects – non-cascading, inner-system cascading, and inter-system cascading – in both independent and interdependent systems. The reviewed literature addresses cascading failures in power systems using diverse methodologies. Baldick et al. (2008) and Gupta et al. (2015) explore probabilistic models and topological simulations for cascading failure analysis in electric power transmission systems, proposing a proactive predictive model based on Support Vector Machine for blackout events in smart grids. Pi et al. (2018) utilize Bayesian networks to predict cascading failure propagation. Hink et al. (2014) and Almalaq and Edwards (2017) address aspects related to the security of power systems using machine learning algorithms for load forecasting in smart grid applications. Other approaches employ simulation-based modelling and analysis techniques to assess the cascading impacts in interdependent networks, such as the work of Korkali et al. (2017) considers a coupled topological model and Smart Grid models, evaluating network performance.

# 4 DESCRIPTION OF THE METHODOLOGY

## 4.1 Overview of the methodology

The primary objective of Task 2.3 is the assessment of the primary types of cascading impacts resulting from multi-hazard interactions across European regions.
Within Task 2.3 of the MEDiate project, our methodology for assessing cascading impacts is structured into five phases. Firstly, data collection involves literature reviews on cascading impacts and machine learning, selection of sectors for analysis, hazards, and disaster databases. Data pre-processing includes enriching databases with contextual data, analysing correlations, and conducting sensitivity analyses.
The methodology employed in Task 2.3 is grounded in ML algorithms capable of discerning patterns in data and leveraging them to predict outcomes for new data (Bishop, 2006).

Machine learning algorithm selection and validation involve a two-step process: identifying algorithms well-suited to the task and then evaluating their performance based on accuracy and computational efficiency (runtime). Subsequent phases involve identifying direct and indirect impacts, modelling dependencies, propagating impacts between sectors, and validating results through testbeds and case studies. Dependencies between CIs are identified through literature reviews and analyses of past events.

Below a schematic overview of the main components of the proposed methodology is reported:

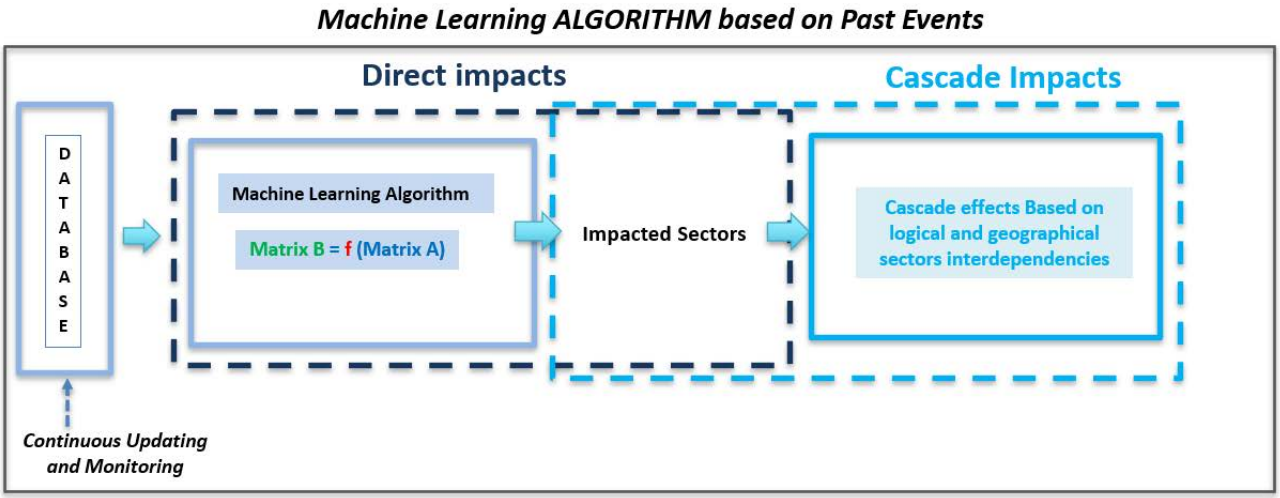



Figure 4.1: Main workflow of the methodology presented in Task 2.3

The process requires a constantly evolving database of past events for model training and testing. Subsequently, this algorithm can be employed to forecast the impacts of future events. Finally, from the first group of directly impacted sectors the cascading impacts on the remained sectors are determined using geographical and logical dependencies, as reported in Figure 4.1. These aspects will be further discussed in the next chapters.
A significant challenge for applying ML to cascading impact assessment lies in data scarcity. Unlike some fields, historical data on cascading impacts is often limited, making it difficult to train effective ML models. This scarcity is further compounded by the complex nature of cascading events themselves, which can be difficult to capture and measure consistently. While the global data landscape is constantly growing, data relevant to cascading impacts may be missing, poorly defined, or unreliable. (Wagenaar, 2020).
Unlocking the full potential of ML in this area requires a multi-pronged approach. Firstly, new data collection methods specifically designed for cascading impacts are needed. Secondly, establishing standardized data collection protocols across various organizations and stakeholders is crucial. Finally, fostering a culture of data sharing among these diverse groups is essential.

The MEDiate methodology in Task 2.3 considers input from stakeholders regarding relevant assets and infrastructure for each testbed via workshops and interviews.
As shown in Figure 4.2, an event triggers direct consequences in related systems. However, these are not considered cascading effects unless they cause further impacts. Cascading effects require a chain reaction where the initially affected system (originating system) disrupts another system that relies on it (dependent system). These initial cascading effects, "first-order cascading effect" denote the immediate repercussions rippling through interconnected systems.

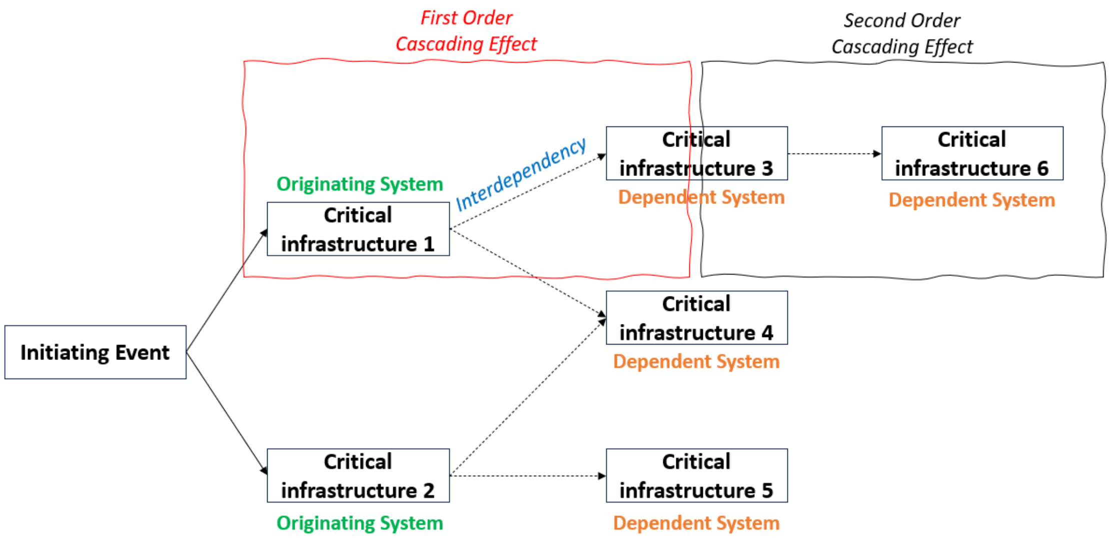



Figure 4.2: Scheme of the propagation of cascading impacts

The decision to halt the analysis at the first order in the Task 2.3 MEDiate methodology is justified by the focus on immediate and direct repercussions stemming from the initiating event. By concentrating on first order cascading effects, the methodology explored the initial impacts that swiftly transfer from the originating systems directly affected by the event to the dependent systems. The decision to limit the analysis to the first order was based on the need to prioritise and thoroughly understand the immediate impacts before considering higher-order consequences. If instead of a linear progression, a loop of effects ensues within the cascading impacts, it introduces a dynamic and potentially more complex scenario. A looped cascading effect can signify a continuous cycle of reciprocal influences and feedback mechanisms among various systems. Adaptive strategies should be formulated in other WPs of MEDiate, taking into account these dynamics, trying to identify leverage points where interventions can be most effective.

## 4.2 Phase 1: Data Collection

The initial phase involves defining the inputs required for the analysis, which are informed by the findings of previous literature reviews. It was focused on:

- Definitions of key concepts regarding dependencies between critical infrastructures;
- Methods to assess cascading impacts;
- Machine learning techniques for cascading impacts assessment.

### 4.2.1 Dataset of Critical Infrastructure

Limited studies have explored the spatial patterns of critical infrastructure exposed to natural hazards. Task 2.3 uses as input a publicly available harmonized global spatial dataset for the representation of CI systems

(Nirandjan, 2022). This global dataset is considered a valuable starting point to gain exposure information for cascading impact assessments. The study led by Nirandjan also proposed a Critical Infrastructure Spatial Index (CISI) at the global scale, at a resolution of 0.10 × 0.10 and 0.25 × 0.25 degrees. The CISI is expressed in a dimensionless value ranging between 0 (no CI intensity) and 1 (highest CI intensity). The index aggregates high resolution geospatial information on multiple CI assets per CI system.

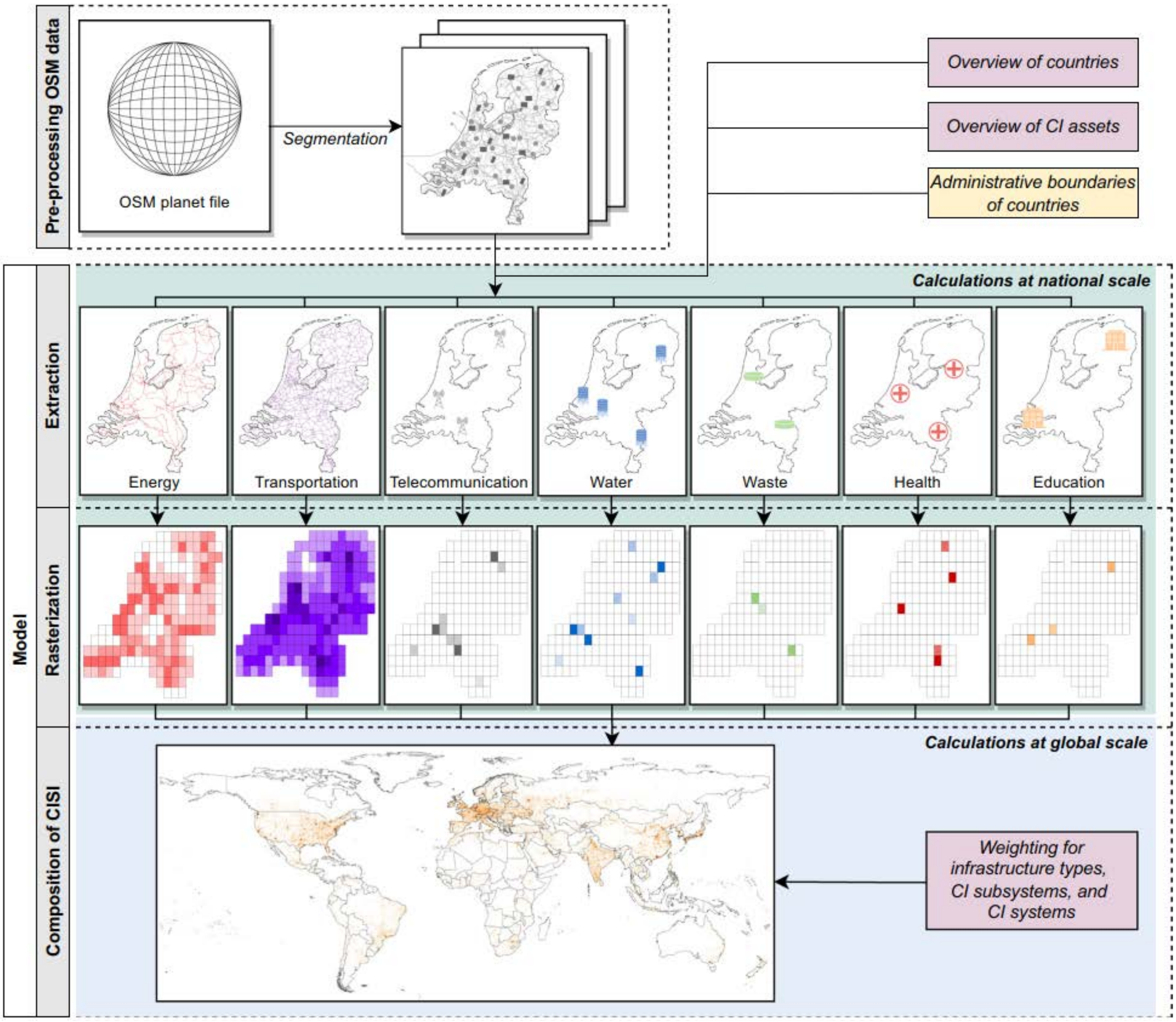



Figure 4.3: Schematic display of workflow (Nirandjan, 2022: p.3)

The green panel in the Figure 4.3 represents the part of the model that performs calculations at a national scale, and the blue panel represents the part of the model that performs calculations at a global scale. On the right-side, the purple-coloured boxes show the specifications required for the model. The yellow box indicates the spatial input required. For the development of the CISI index, Nirandjan selected 39 CI types and categorised them under seven overarching CI systems (Table 4.1):

- transportation,
- energy,
- telecommunication,
- waste,
- water,
- education and
- health.

To validate the CISI, the author compared it with subnational data on Gross Domestic Product (GDP) and population distribution. Finally, the geospatial information on CI was transformed into a consistent raster of the globe with a resolution of 0.10 × 0.10 degrees, which is approximately 11.1 × 11.1 km at the equator, and a second raster with a resolution of 0.25 × 0.25 degrees. The spatially-explicit harmonized global dataset of CI is publicly available from the Zenodo repository (https://doi.org/10.5281/ZENODO.4957647). The global database is provided in standard WGS84 coordinate system at multiple resolutions: 0.10 × 0.10 and 0.25 × 0.25 degrees in GeoTIFF format.

Table 4.1: List of infrastructure types considered in this study, categorised under seven CI sectors and ten subsectors (Nirandjan, 2022)

| Sector | Subsector | Infrastructure type | Raster filename | |
|---|---|---|---|---|
| Energy | Power | Cable | summary_energy.feather | cable.tif |
| | | Line | | line.tif |
| | | Minor line | | minor_line.tif |
| | | Plant | | plant.tif |
| | | Substation | | substation.tif |
| | | Power tower | | power_tower.tif |
| | | Power pole | | power_pole.tif |
| Transportation | Railways | Railway | summary_transportation.feather | railway.tif |
| | Roads | Primary | | primary.tif |
| | | Secondary | | secondary.tif |
| | | Tertiary | | tertiary.tif |
| | Airports | Airport | | airports.tif |
| Telecommunication | Telecom | Communication tower | summary_telecommunication.feather | communication_tower.tif |
| | | Mast | | mast.tif |
| Water | Water supply | Water tower | summary_water.feather | water_tower.tif |
| | | Water well | | water_well.tif |
| | | Reservoir covered | | reservoir_covered.tif |
| | | Water works | | water_works.tif |
| | | Reservoir | | reservoir.tif |
| Waste | Solid waste | Landfill | summary_waste.feather | landfill.tif |
| | | Waste transfer station | | waste_transfer_station.tif |
| | Water waste | Water waste treatment plant | | wastewater_treatment_plant.tif |
| Health | Healthcare | Clinic | summary_healthcare.feather | clinic.tif |
| | | Doctors | | doctors.tif |
| | | Hospital | | hospitals.tif |
| | | Dentist | | dentist.tif |
| | | Pharmacy | | pharmacy.tif |

| | | | | |
|---|---|---|---|---|
| | | Physiotherapist | | physiotherapist.tif |
| | | Alternative | | alternative.tif |
| | | Laboratory | | laboratory.tif |
| | | Optometrist | | optometrist.tif |
| | | Rehabilitation | | rehabilitation.tif |
| | | Blood donation | | blood_donation.tif |
| | | Birthing center | | birthing_center.tif |
| Education | Education | College | summary_education.feather | college.tif |
| | | Kindergarten | | kindergarten.tif |
| | | Library | | library.tif |
| | | School | | school.tif |
| | | University | | university.tif |

Figure 4.4 and 4.5 show an elaboration carried out using the Qgis software of the data published by Nirandjan's work representing primary roads and power towers for Europe.

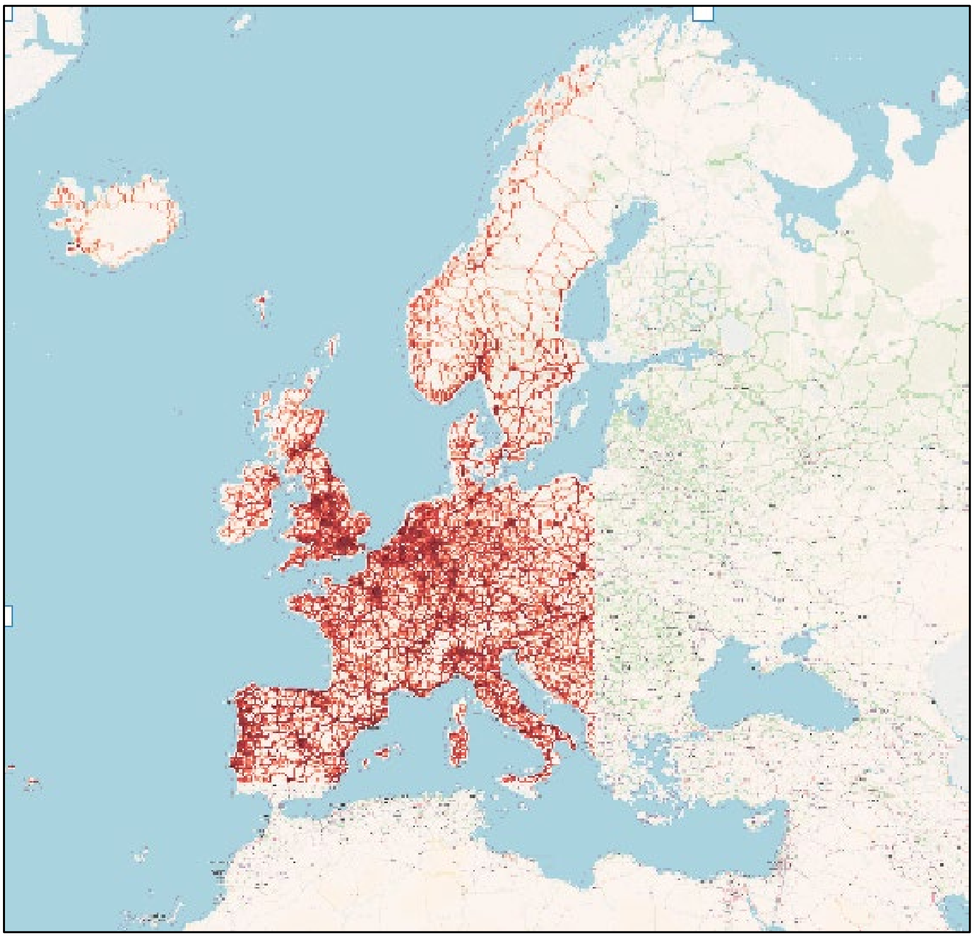


Figure 4.4: Representation of primary roads in Europe (adapted from Nirandjan, 2022)

Figure 4.5: Representation of primary roads in Europe. (adapted from Nirandjan, 2022)

This global dataset of critical infrastructure (Nirandjan, 2022) was used to assess cascading impacts on roads network and power network.

### 4.2.2 Database Selection

In recent years the international community has made significant advances in improving the documentation of losses from natural hazards. These advancements are first and foremost visible in the significantly increased number of countries that now operate disaster loss databases, either through governmental, non-governmental, academic and/or private organisations (IRDR, 2014).

For many databases data gaps are common. There are gaps regarding: i) temporal coverage with missing years and/or months; ii) spatial coverage with missing reports from some regions, communities, etc.; iii) loss estimation with no losses reported for some events, particularly low impact/high frequency events; and iv) loss indicators with inconsistent completeness across events.

At present there are six global loss databases EM DAT, GLIDE, DesInventar, SHELDUS, NatCatSERVICE, Sigma, of which the latter two have limited public accessibility.

The following table (Table 4.2) compares the main characteristics of the principal global and national loss databases.

Table 4.2: Global loss databases comparison

| | EM-DAT | NatCatSERVICE | Sigma | GLIDE | DesInventar | SHELDUS |
|---|---|---|---|---|---|---|
| **URL** | https://public.emdat.be/ | | | http://www.glidenumber.net/ | http://www.desinventar.org/ | http://www.sheldus.org/ |
| **Owner** | Centre for Research on the Epidemiology of Disasters (CRED), Université Catholique de Louvain, Belgium | Munich Re, Germany | Swiss Re, Switzerland | Asian Disaster Reduction Center (ADRC), Japan | Varies by country | Hazards and Vulnerability Research Institute (HVRI), University of South Carolina, USA |
| **Audience** | Humanitarian community, academia | General public, insurance industry | General public, insurance industry | Loss database operators | Emergency management, hazard mitigation planning, academia | Emergency management, hazard mitigation planning, academia |
| **Spatial Coverage** | Global | Global | Global | Global | National | National (US) |
| **Temporal Coverage** | 1900 – present | 79 AD – present | | 1930 – present | Varies by country, more than 30 countries operate DesInventar databasess | 1960 – present |
| **Number of Records** | >20,000 | >33,000 | | >5,000 | Varies by country | >800,000 |
| **Recording Thresholds** | ≥10 fatalities, ≥100 affected, declaration of state of emergency, or call for international assistance | | | ≥10 fatalities, ≥100 affected, declaration of state of emergency, or call for international assistance | ≥1 human loss or ≥$1 in economic loss | ≥1 human loss or ≥$1 in economic loss |

Table 4.3 shows the main advantages and disadvantages of each database. All the databases have in common:

- a lack of detailed disaggregated data of urban areas to allow for an analysis of small area units and identification of informal settlers in urban areas

a lack of collated disaster datasets to show accurate losses.

Table 4.3: Disaster Global loss databases at a glance – Loss indicators and hazard coverage

| | | EM-DAT | NatCatSERVICE | Sigma | GLIDE | DesInventar | SHELDUS |
|---|---|---|---|---|---|---|---|
| Loss Indicators | Killed | X | | X | | X | X |
| | Injured | X | X | X | | X | X |
| | Missing | | X | X | | X | |
| | Homeless | X | | X | | X | |
| | Affected | X | X | X | | | |
| | Evacuated | | X | | | X | |
| | Relocated | | | | | X | |
| | Displaced | | X | | | | |
| | Property Loss | X | | | | | X |
| | Crop Loss | X | | | | | X |
| | Environmental Loss | X | | | | | |
| | Insured Loss | | X | X | | | |
| | Aggregate Economic Loss | X | X | | | X | |
| | Infrastructure Damage | X | X | | | X | |
| | Economic Sector Damage | X | X | | | X | |
| Hazard Coverage | Geophysical | X | X | X | X | X | X |
| | Hydrological | X | X | X | X | X | X |
| | Meteorological | X | X | X | X | X | X |
| | Climatological | X | X | X | X | X | X |
| | Biological | X | | | X | X | |
| | Technological | X | | X | X | X | |
| | Terrorism | | | X | | | |

Starting from the comparison between the loss databases (Table 4.4), DesInventar (http://www.DesInventar.net/methodology.html) has been selected for the development of the machine learning for the following reasons:

- The events are geolocated: this is a crucial aspect to enable the analysis to be carried out;
- provides the damage of a large set of sectors;
- The collection of historical disaster losses data is provided in a systematic and homogeneous manner at a low administrative level based on a pre-defined set of definitions and classifications.

Table 4.4: Disaster Global loss databases at a glance – Advantages and limitations

| | EM-DAT | NatCatSERVICE | Sigma | GLIDE | DesInventar | SHELDUS |
|---|---|---|---|---|---|---|
| **Advantages** | - Actively and constantly maintained<br>- Human losses are disaggregated into deaths, injured, affected, homeless.<br>- Data is to be stored in a uniform format.<br>- The threshold to record is clear.<br>- Users can download the dataset itself. | - Reliable information on insured losses<br>- Graphics can be obtained based on the statistical data by clicking. | - Reliable information on insured losses<br>- Graphics can be obtained based on the statistical data by clicking. | | - Widely used tool<br>- Human losses are disaggregated into deaths, injured, affected, homeless.<br>- Data is to be stored by each country in a uniform format developed to record disaggregated data.<br>- UNISDR encourages countries to use DesInventar in implementing the SFDRR.<br>- Users can download the dataset itself. | |
| **Limitations** | the definition of "affected people" of EM-DAT and other existing databases is vaguer than that of SFDRR and results in overestimation of affected people | information accessibility is limited | information accessibility is limited | | - a lack of connections between disaster loss and data of underlying causes such as social and environmental factors - Spatial coverage of DesInventar is limited in sub-Saharan Africa | |
| | - missing observations and damage reports over time | | | | The data categories in SFDRR indicators and DesInventar do not capture indirect disaster impacts | |
| | disaster damages to infrastructure and agriculture are poorly captured | | | | | |
| | a lack of detailed disaggregated data of urban areas to allow for an analysis of small area units and identification of informal settlers in urban areas | | | | | |

DesInventar is a conceptual and methodological tool for the generation of National Disaster Inventories and the construction of databases of damage, losses and in general the effects of disasters. The basic criteria guiding the construction of DesInventar are:

- All inventories must use the same variables to measure the effects and the same homogeneous and basic classification of events.
- The information compiled and processed must be entered in a scale of time and at a geo-referenced spatial level.
- The information comprising DesInventar inventories must be spatially disaggregated in order to show (and later analyse) the effects of disasters at local level. For country level disaster inventories, it is recommended a minimum disaggregation level equivalent to Municipality, usually one or two levels below the first administrative/political division (Province/State/Department, depending on each country).
- The inventories can then be analysed following a number of existing and emerging methodologies, starting with the Preliminary Analysis Methodology, which give users an immediate understanding of the impact of disasters in a country or region, the possibilities of comparative research and support to decision-making processes related to risk reduction actions including risk assessments and risk management as a whole.

DesInventar focuses on the consequences of disasters within a specific area. These impacts, representing the sum of losses or negative effects, serve as indicators of vulnerability in communities, regions, and countries. To systematically assess these impacts, DesInventar employs a standardized classification scheme with four categories:

1. People: This category captures impacts on people, such as casualties, injuries, and displacement.
2. Homes: This category focuses on impacts on housing units, including damage and destruction.
3. Infrastructure: This category includes impacts on infrastructure systems, such as damage to roads, bridges, and power grids.
4. Economic Losses: This category captures economic losses caused by the disaster, such as loss of crops, livestock, and business disruption.

The countries were the DesInventar methodology has been applied are shown in Figure 4.6. Only countries with available event location data were included in the analysis.

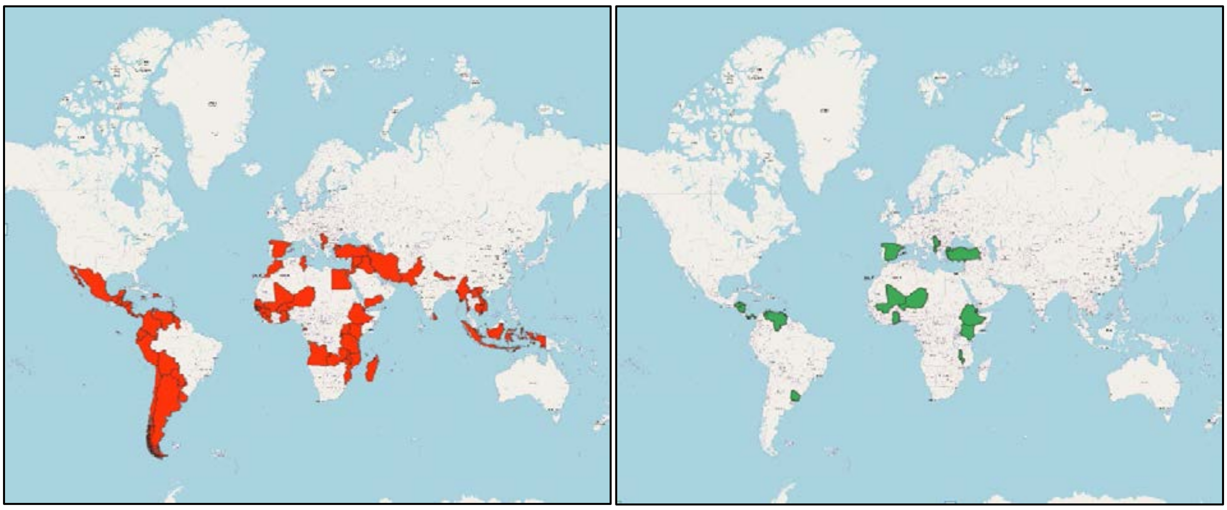


Figure 4.6: Left panel: Countries and regions available within DesInventar (adapted from https://www.desinventar.net/). Right panel: Countries with the location of impacts (adapted from https://www.desinventar.net/)

### 4.2.3 Hazards selection

Selecting the initiating events is crucial for any cascading impact assessment. This choice determines the scope of the analysis and the types of cascading impacts considered.

In Task 4.5 three multi-hazard interactions for each testbed were selected.

Table 4.5: Identified multi-hazards of importance to each testbed.

| Testbed | Multi-hazard interactions | Typology |
|---|---|---|
| Oslo | 1. Compound flood (coastal and riverine) | Multivariate |
| | 2. Flood and quick clay | Preconditioned and triggering |
| | 3. Flood and landslide | Triggering |
| Nice | 1. Compound flood (coastal and riverine) | Multivariate |
| | 2. Flood and landslide | Triggering |
| | 3. Extreme heat and drought | Temporally compounding |
| Essex | 1. Extreme wind and rainfall | Spatially compounding |
| | 2. Compound flood (coastal and riverine) | Multivariate |
| | 3. Extreme heat and rainfall | Spatially compounding |
| Múlaþing | 1. Heavy rain and landslide | Preconditioned and triggering |
| | 2. Snow melt and flood | Preconditioned and triggering |
| | 3. Heavy snowfall and avalanche | Preconditioned and triggering |

The multi-hazards have been split in single hazards to find a correlation with the ones defined within DesInventar (Table 4.6).

Table 4.6: Hazard linkage for the analysis

| MEDIATE_SINGLE-HAZARD | DESINVENTAR CORRELATION |
|---|---|
| avalanche | Avalanche |
| drought | Drought |
| extreme heat | Heat Wave |
| extreme wind | Windstorm |
| flood | Flood and Flash-flood |
| heavy rain | Rain |
| rainfall | |
| heavy snowfall | Snowfall |
| snow melt | |
| Quick clay (assumption = landslide) | Landslide |

The following figure summarises the available historical events from DesInventar with a reported impact for each hazard type:

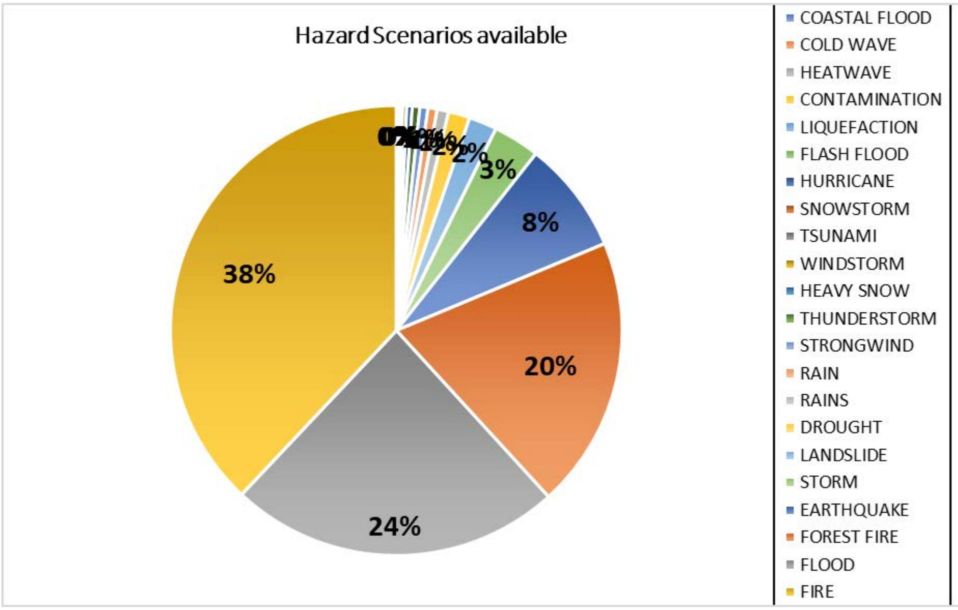



Figure 4.7: Availability of the hazard from DesInventar

The figure 4.7 shows available hazard information from DesInventar respectively for fire (38%), flood (24%), forest fire (20%), earthquake (8%). While the lowest are due to heat wave. This highlights the limitations of the database, which influences the results of the analysis.
DesInventar allows to consider the multi-hazard interaction using the analysis module choosing a different "Cause", as the following figure 4.8 shows.

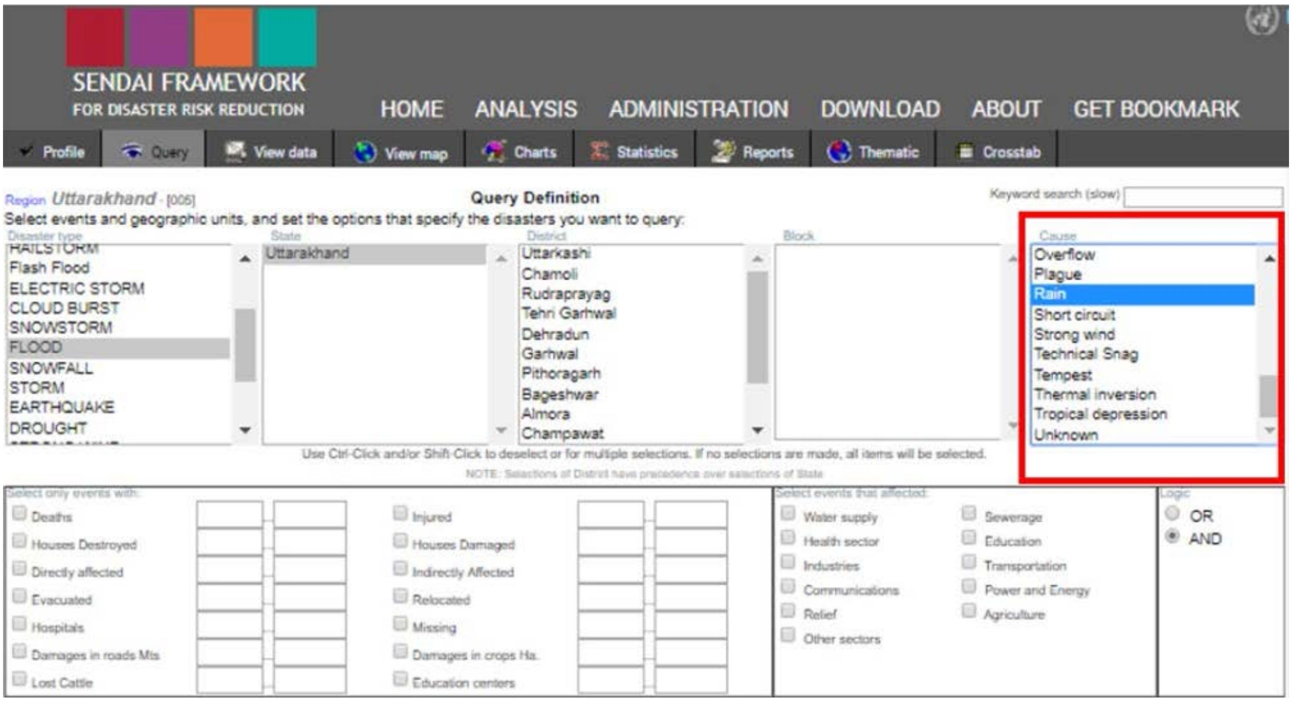



Figure 4.8: DesInventar interface for the choice of a hazard and its cause

## 4.3 Phase 2: Data Pre-processing

Data pre-processing stands as an essential phase within the machine learning pipeline, tasked with reshaping raw data into a format optimized for model training. Its primary objective lies in enhancing the integrity of the input data, ultimately fostering improved model performance. Below are several prevalent methodologies employed in data pre-processing:

- *Handling Missing Values*: Missing values are a common occurrence in real-world datasets. Techniques for handling missing values include imputation (replacing missing values with a calculated estimate), deletion (removing rows or columns with missing values), or using algorithms that can handle missing values directly.
- *Data Cleaning*: This involves correcting or removing errors in the data. It may include tasks such as removing duplicate records, correcting inconsistent values, or dealing with outliers. In Disinventar, different scenarios are devoid of accurate location information. Then, those scenarios are not considered in the final database used for the ML algorithms.
- *Feature Scaling:* Features in the dataset may have different scales, which can negatively impact the performance of some machine learning algorithms.
- *Feature Encoding:* Categorical variables need to be converted into numerical format for many machine learning algorithms to work effectively. One-hot encoding, label encoding, and binary encoding are some common techniques for encoding categorical variables. For this reason, the event type (i.e. "FIRE") cannot be considered in Matrix A.
- *Feature Selection:* In datasets with a large number of features, not all features may be relevant for model training. Feature selection techniques help identify the most important features that contribute to the predictive power of the model, thereby reducing dimensionality and potentially improving model performance and training time. In fact, various strategies have been explored to enhance the database. Initially, all the data linked to the TIFFs are taken into account. After, only some of them have been selected through a logical selection process.
- *Feature Engineering:* This involves creating new features from the existing ones that may improve the model's performance. It could include transformations, combinations, or other operations on the existing features to extract more meaningful information. This technique has been considered in the output Matrix, where the impacted sectors have been identified transforming and using information of other sections (i.e. for the impact on the residential sector the number of damaged houses or destroyed houses have been merged).
- *Normalization:* Normalization ensures that all features have a similar scale. This is particularly important for algorithms that are sensitive to the scale of the input features, such as neural networks and k-nearest neighbors (KNN).
- *Data Splitting:* Before training a model, the dataset is typically split into training, validation, and test sets. This ensures that the model's performance can be evaluated on unseen data and helps prevent overfitting. This approach has been evaluated accross in the all the algorithm types tested in this study.

The selected database DesInventar lacked the ability to depict the specific scenario due to the absence of Intensity measures or associated engineering parameters. Therefore, the scenarios were enriched by incorporating information from the tiff files considering different geographical areas (i.e. Europe, etc.) and additional contextual data, providing more comprehensive insight into the exposure of assets surrounding the event location. This led to an enhancement in the correlation between the Input Matrix and the output matrix. Various approaches have been contemplated for constructing the input Matrix. Initially, different world regions were considered, such as solely European nations, followed by a combination of Europe and America, and ultimately both regions together.
Subsequently, diverse strategies were explored concerning data enrichment. Initially, all data pertaining to various sub-sectors (defined in Table4.1) were taken into account. Subsequently, these data underwent multiple filtering processes to ascertain their impact on the algorithm's training and testing phases. The information contained in the different tiffs is outlined in Table 4.7.

Table 4.7: Filtering process example

| System | Subsystem | Infrastructure type | Raster filename | |
|---|---|---|---|---|
| Energy | Power | Cable | summary_energy.feather | cable.tif |
| | | Line | | line.tif |
| | | Minor line | | minor_line.tif |
| | | Plant | | plant.tif |
| | | Substation | | substation.tif |
| | | Power tower | | power_tower.tif |
| | | Power pole | | power_pole.tif |
| Transportation | Railways | Railway | summary_transportation.feather | railway.tif |
| | Roads | Primary | | primary.tif |
| | | Secondary | | secondary.tif |
| | | Tertiary | | tertiary.tif |
| | Airports | Airport | | airports.tif |
| Telecommunication | Telecom | Communication tower | summary_telecommunication.feather | communication_tower.tif |
| | | Mast | | mast.tif |
| Water | Water supply | Water tower | summary_water.feather | water_tower.tif |
| | | Water well | | water_well.tif |
| | | Reservoir covered | | reservoir_covered.tif |
| | | Water works | | water_works.tif |
| | | Reservoir | | reservoir.tif |
| Waste | Solid waste | Landfill | summary_waste.feather | landfill.tif |
| | | Waste transfer station | | waste_transfer_station.tif |
| | Water waste | Water waste treatment plant | | wastewater_treatment_plant.tif |
| Health | Healthcare | Clinic | summary_healthcare.feather | clinic.tif |
| | | Doctors | | doctors.tif |
| | | Hospital | | hospitals.tif |
| | | Dentist | | dentist.tif |
| | | Pharmacy | | pharmacy.tif |
| | | Physiotherapist | | physiotherapist.tif |
| | | Alternative | | alternative.tif |
| | | Laboratory | | laboratory.tif |
| | | Optometrist | | optometrist.tif |
| | | Rehabilitation | | rehabilitation.tif |
| | | Blood donation | | blood_donation.tif |
| | | Birthing center | | birthing_center.tif |
| Education | Education | College | summary_education.feather | college.tif |
| | | Kindergarten | | kindergarten.tif |
| | | Library | | library.tif |
| | | School | | school.tif |
| | | University | | university.tif |

Another aspect considered in constructing the training dataset involves the unique behaviour of each hazard across various sectors, as well as the distinct parameters required for their identification. Consequently, the database containing scenarios has been divided for each hazard type, and associated algorithms have been executed accordingly.

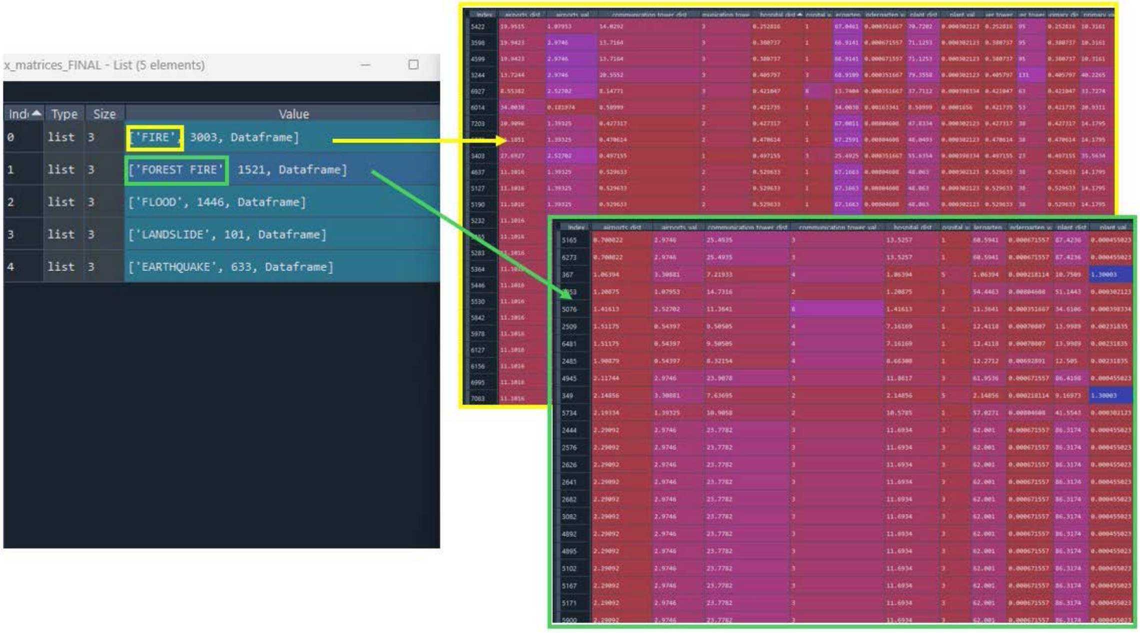



Figure 4.9: Database partitioning for different hazards

The tiff files contain information regarding the location of the sub-sector asset and an indication of its importance.
We initially considered a combined analysis of two factors: distance of subsector assets from the event location and their significance values. However, we later separated them for individual examination..

## 4.4 Phase 3: Model Selection and Validation

In machine learning, different types are distinguished based on learning paradigms or data characteristics. Primary types include Supervised, Unsupervised, Semi-Supervised, Reinforcement, and Deep Learning. In this context, supervised learning is under consideration.
In supervised learning, the algorithm learns from labeled data, where each training example is paired with the correct output. The objective is to establish a mapping from inputs to outputs.
In fact, this study aims to explore the correlation between the description of scenarios (giving an idea about the hazard, vulnerability, and exposure) and the sectors affected. Supervised learning algorithms align well with this objective.
Numerous algorithms and computational techniques are employed in the supervised learning process. Here are some common types of supervised learning algorithms:

- Regression (Linear and Logistic Regression)
- Naïve Bayes
- Classification.

As the Naïve Bayes algorithms works independently that means that the presence of one feature will not impact the other has been neglected as is not aligned with the purpose of this task.
Instead, Linear Regression and Classification (in this case Multiclass Classification) has been considered.

Linear regression is utilized to discern the relationship between two variables, often employed for predicting future outcomes. Additionally, linear regression can be categorized based on the number of independent and dependent variables involved. For instance, if there is one independent and one dependent variable, it is known as simple linear regression. Meanwhile, if there are two or more independent and dependent variables, it is called multilinear regression. As in this case multiple independent and dependent variables are considered a Multilinear Regression Method is used.

Classification is a type of supervised learning algorithm that accurately assigns data into different categories or classes. It recognizes specific entities and analyses them to conclude where those entities must be categorized. This algorithm was considered as the final output of the ML is the assignment of 0 and 1 to the different sectors that mean if a sector is impacted or not. Some of the classification algorithms are as follows:

- K-nearest neighbor
- Random forest
- Support vector machines (SVM)
- Decision tree
- Linear classifiers.

In Task 2.3, the KNN, Random Forest and Support Vector Machine have been considered. These algorithms have been performed with Python programming language. In Python there are different libraries associated to the different algorithms. For each of these algorithms, starting from the main database containing the collected events, a training and test set of scenarios are taken into account (Figure 4.10). Thus, the database is partitioned both horizontally and vertically. In the horizontal direction to consider the division in Matrix A and B. In the vertical direction to split it for the training and test sets. The training set is essential for training the algorithm, while the test set is used to evaluate the algorithm's performance during the testing phase. The percentage of the test set is not fixed but depends on the type of algorithm being utilised. Figure 4.11 shows and example of the Multilinear Regression Algorithm used. Regarding the Classification algorithms, as part of the results comparison, the accuracy rate and runtime are evaluated to provide insight into the efficiency of the methods (Figure 4.12).

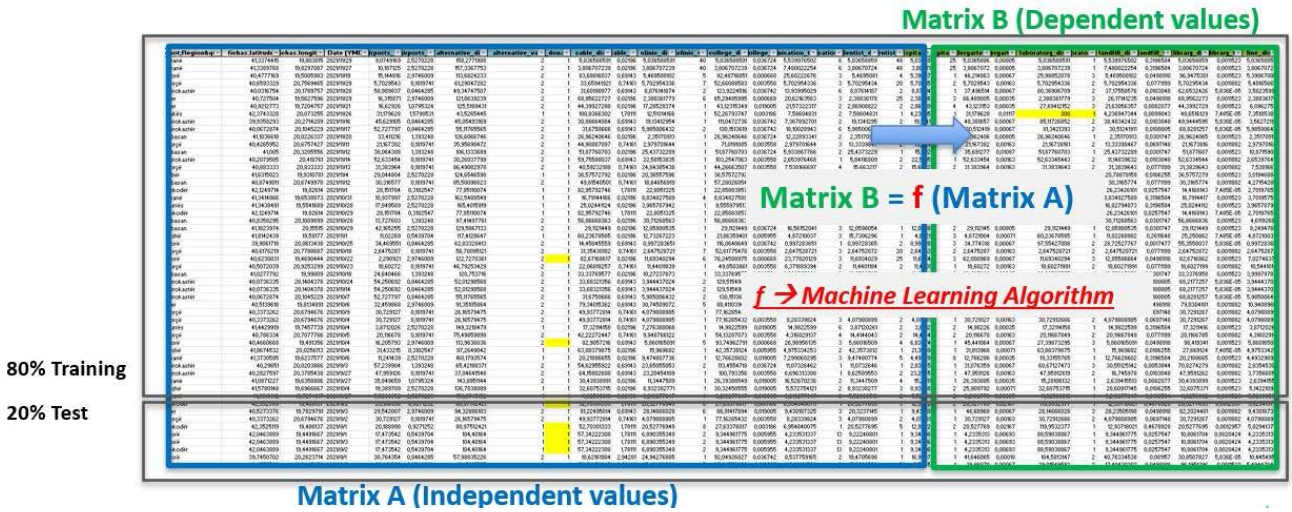



Figure 4.10: Training and test sets

```
''' LINEAR REGRESSION '''
if ML_type=="ml":

    Test_SIZE=0.2
    Lin_Regression=[]
    sets_test_train=[]
    prediction_results_regression=[]
    validation_prediction_regression=[]
    for k,j in enumerate (events[:5]):

        Lin_Regression.append(linear_model.LinearRegression())

        sets_test_train.append(train_test_split(x_matrices_FINAL[k][2],y_matrices_FINAL[k][2],
                                                test_size=Test_SIZE,random_state=4) )
        Lin_Regression[k].fit(sets_test_train[k][0],sets_test_train[k][2])

        result=pd.DataFrame(Lin_Regression[k].predict(sets_test_train[k][1]),
                            columns= y_matrices_FINAL[0][2].columns) # from array to DF

        prediction_results_regression.append([
                j,
                sets_test_train[k][3],
                result
              ])
```

Figure 4.11: Multilinear Regression

| family | model | classification_rate | runtime |
|---|---|---|---|
| KNN | KNN-1-FIRE | 0,4127 | 0,0880 |
| KNN | KNN-1-FOREST FIRE | 0,5000 | 0,0456 |
| KNN | KNN-1-FLOOD | 0,3285 | 0,0757 |
| KNN | KNN-1-LANDSLIDE | 0,2647 | 0,0050 |
| KNN | KNN-1-EARTHQUAKE | 0,4641 | 0,0216 |
| KNN | KNN-1-FIRE | 0,4127 | 0,0872 |
| KNN | KNN-2-FIRE | 0,5469 | 0,0916 |
| KNN | KNN-3-FIRE | 0,5247 | 0,0935 |
| KNN | KNN-4-FIRE | 0,5631 | 0,0915 |
| KNN | KNN-1-FOREST FIRE | 0,5000 | 0,0516 |
| KNN | KNN-2-FOREST FIRE | 0,4263 | 0,0450 |
| KNN | KNN-3-FOREST FIRE | 0,5040 | 0,0457 |
| KNN | KNN-4-FOREST FIRE | 0,4861 | 0,0481 |
| KNN | KNN-1-FLOOD | 0,3285 | 0,0457 |
| KNN | KNN-2-FLOOD | 0,3285 | 0,0530 |
| KNN | KNN-3-FLOOD | 0,2699 | 0,0627 |
| KNN | KNN-4-FLOOD | 0,2762 | 0,0546 |
| KNN | KNN-1-LANDSLIDE | 0,2647 | 0,0040 |
| KNN | KNN-2-LANDSLIDE | 0,3824 | 0,0040 |
| KNN | KNN-3-LANDSLIDE | 0,2941 | 0,0050 |
| KNN | KNN-4-LANDSLIDE | 0,2647 | 0,0040 |
| KNN | KNN-1-EARTHQUAKE | 0,4641 | 0,0210 |
| KNN | KNN-2-EARTHQUAKE | 0,5120 | 0,0216 |
| KNN | KNN-3-EARTHQUAKE | 0,4976 | 0,0210 |
| KNN | KNN-4-EARTHQUAKE | 0,5311 | 0,0239 |
| RF | RF-10-FIRE | 0,5379 | 0,0560 |
| RF | RF-100-FIRE | 0,5379 | 0,4758 |
| RF | RF-1000-FIRE | 0,5340 | 4,9706 |
| RF | RF-10-FOREST FIRE | 0,5354 | 0,0316 |
| RF | RF-100-FOREST FIRE | 0,6010 | 0,3438 |
| RF | RF-1000-FOREST FIRE | 0,5801 | 3,7648 |
| RF | RF-10-FLOOD | 0,3149 | 0,0389 |
| RF | RF-100-FLOOD | 0,3370 | 0,3410 |
| RF | RF-1000-FLOOD | 0,3619 | 3,3082 |
| RF | RF-10-LANDSLIDE | 0,3462 | 0,0255 |
| RF | RF-100-LANDSLIDE | 0,4231 | 0,0815 |
| RF | RF-1000-LANDSLIDE | 0,3077 | 0,8366 |
| RF | RF-10-EARTHQUAKE | 0,4843 | 0,0189 |
| RF | RF-100-EARTHQUAKE | 0,5157 | 0,1690 |
| RF | RF-1000-EARTHQUAKE | 0,5094 | 1,4749 |
| SVM | FIRE | 0,3968 | 0,0034 |
| SVM | FOREST FIRE | 0,3701 | 0,0000 |
| SVM | FLOOD | 0,1271 | 0,0010 |
| SVM | LANDSLIDE | 0,2308 | 0,0000 |
| SVM | EARTHQUAKE | 0,3270 | 0,0010 |

Figure 4.12: Accuracy and runtime of Multiclass Classification

After evaluating various algorithms, it was found that multilinear regression provides more accurate results compared to others. Indeed, with this method, it is feasible to obtain, for a given scenario, the probability that a sector is impacted or not. Instead, with the Classification method a value of 0 (not impacted) and 1 (impacted) is given. Since predictions are made for future potential scenarios, it makes more sense to provide probabilities rather than definite impacts on sectors.

## 4.5 Phase 4: Direct Impacts

The direct impact phase of the methodology consists in the identification of the direct impacted sectors starting from the knowledge of the scenario and its context with the ML approach. From this first phase the direct impacted sectors are obtained considering a geographical dependency (Rinaldi, 2001). Then, starting from the directly impacted sectors, is possible to foresee the subsequent cascading effects over the other remained sectors considering a geographical and logical process.

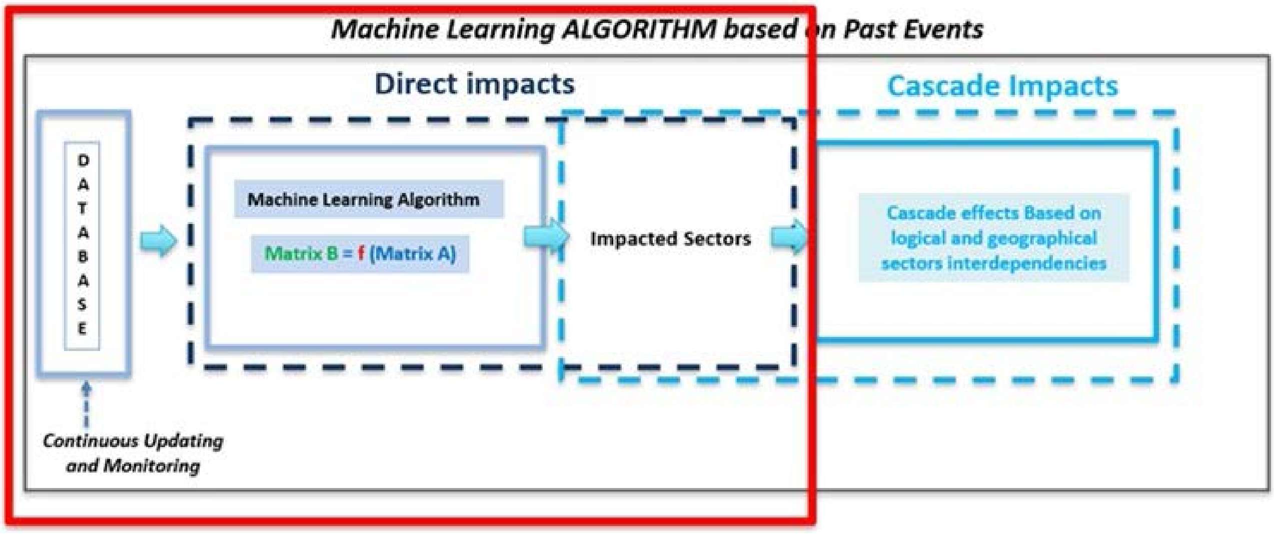



Figure 4.13: Phase 4 – Direct impacts

The ML is carried out using Multilinear Regression.
Below a comparison between the actual values of the test set is reported (representing the real results of the considered database regarding the impacts on sectors) and the predicted impacts obtained through ML when considering the same event.

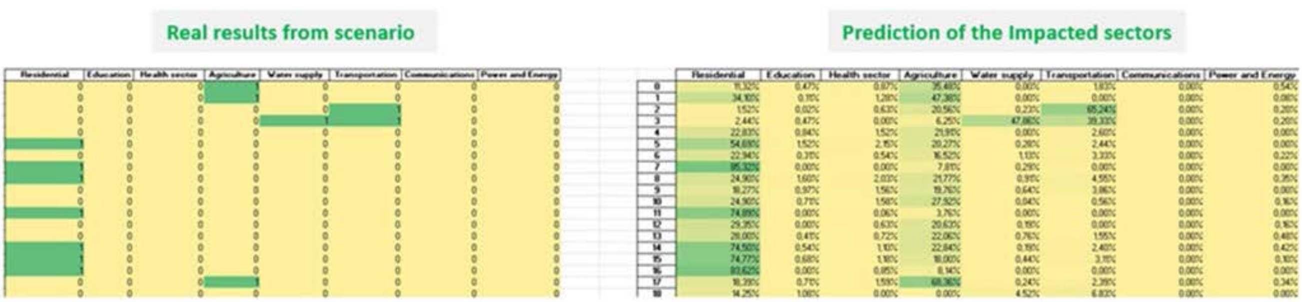
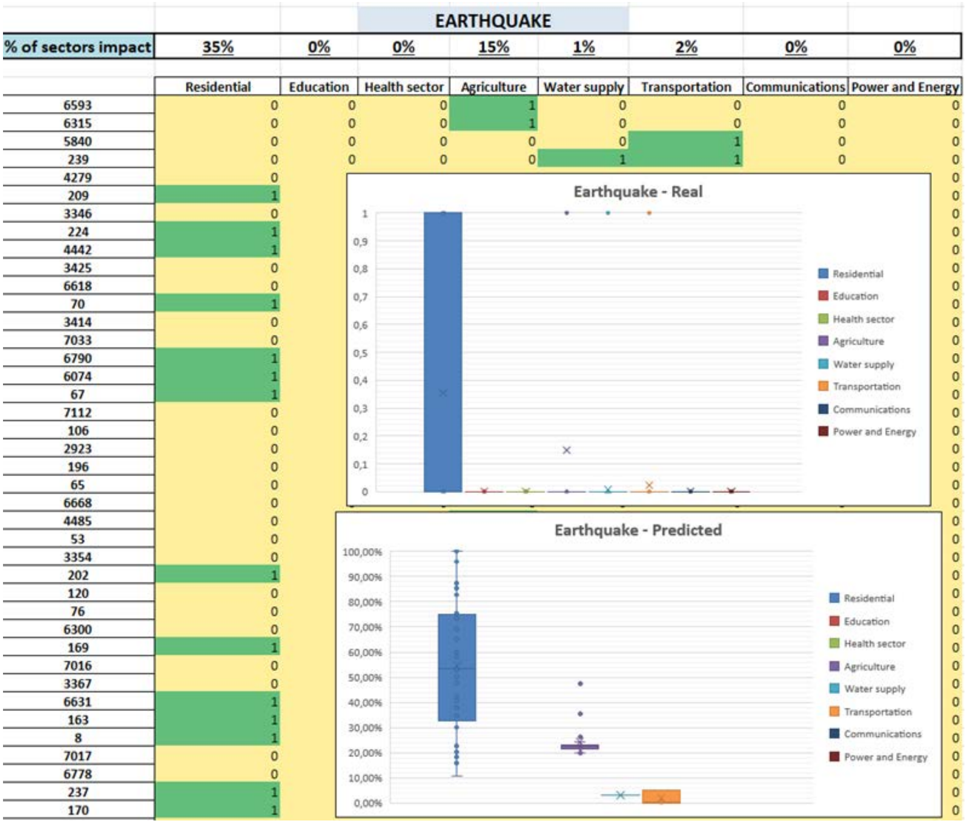
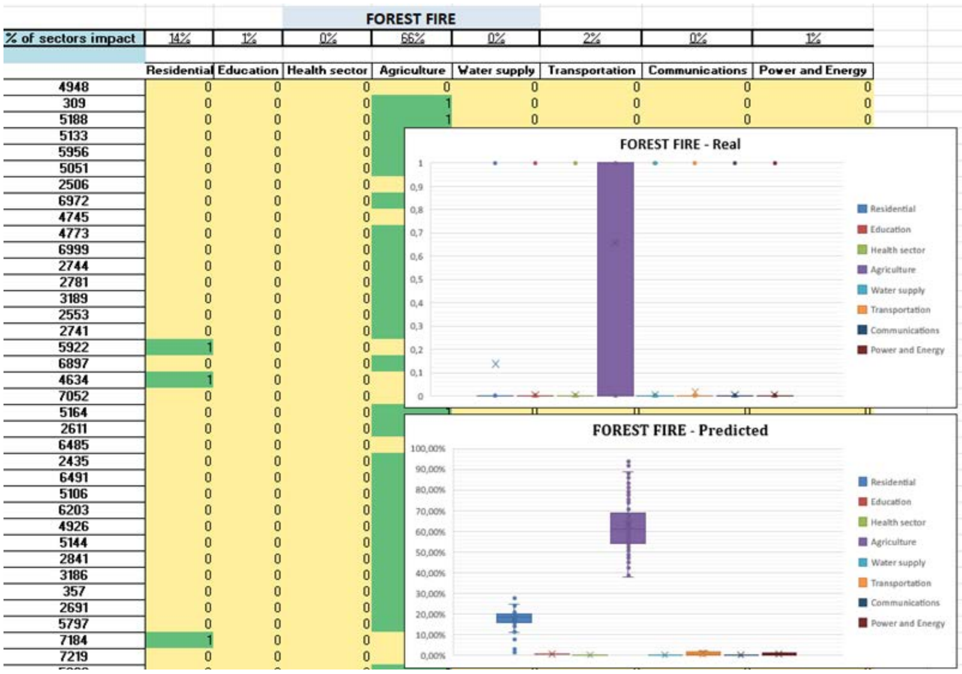
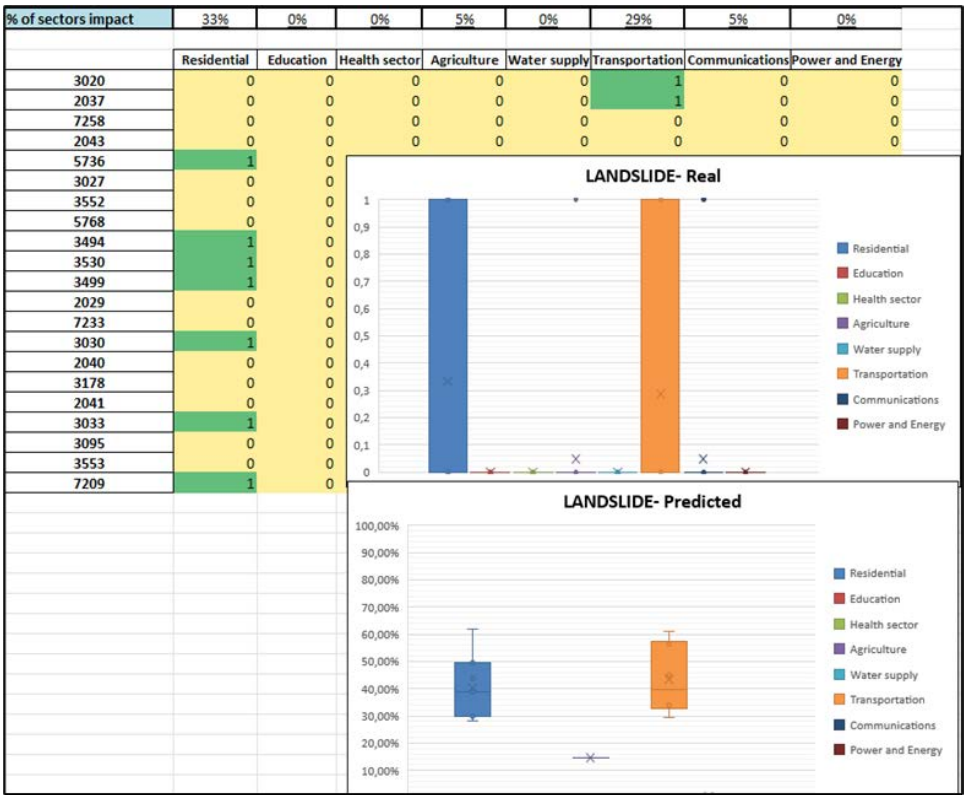



Figure 4.14: Results comparison


EARTHQUAKE
% of sectors impact
35%
0%
0%
15%
1%
2%
0%
0%
Residential
Education
Health sector
Agriculture
Water supply
Transportation
Communications
Power and Energy
Earthquake - Real
Earthquake - Predicted
Residential
Education
Health sector
Agriculture
Water supply
Transportation
Communications
Power and Energy


FOREST FIRE
% of sectors impact
14%
1%
0%
66%
0%
2%
0%
1%
Residential
Education
Health sector
Agriculture
Water supply
Transportation
Communications
Power and Energy
FOREST FIRE - Real
FOREST FIRE - Predicted
Residential
Education
Health sector
Agriculture
Water supply
Transportation
Communications
Power and Energy



| % of sectors impact | 33% | 0% | 0% | 5% | 0% | 29% | 5% | 0% |
|---|---|---|---|---|---|---|---|---|
| | Residential | Education | Health sector | Agriculture | Water supply | Transportation | Communications | Power and Energy |
| 3020 | 0 | 0 | 0 | 0 | 0 | 1 | 0 | 0 |
| 2037 | 0 | 0 | 0 | 0 | 0 | 1 | 0 | 0 |
| 7258 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 |
| 2043 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 |
| 5736 | 1 | 0 | | | | | | |
| 3027 | 0 | 0 | | | | | | |
| 3552 | 0 | 0 | | | | | | |
| 5768 | 0 | 0 | | | | | | |
| 3494 | 1 | 0 | | | | | | |
| 3530 | 1 | 0 | | | | | | |
| 3499 | 1 | 0 | | | | | | |
| 2029 | 0 | 0 | | | | | | |
| 7233 | 0 | 0 | | | | | | |
| 3030 | 1 | 0 | | | | | | |
| 2040 | 0 | 0 | | | | | | |
| 3178 | 0 | 0 | | | | | | |
| 2041 | 0 | 0 | | | | | | |
| 3033 | 1 | 0 | | | | | | |
| 3095 | 0 | 0 | | | | | | |
| 3553 | 0 | 0 | | | | | | |
| 7209 | 1 | 0 | | | | | | |



Figure 4.15:-:Comparison between Real impacts and predicted impacts

As reported in Figure 4.15 the predicted impact values are closer to the real impacts rather than the statistical percentage of occurrence (reported in the first line of the figure There are still some errors in the algorithm, indicating that more scenarios are required, especially as the number of considered data for the description of the event increases.

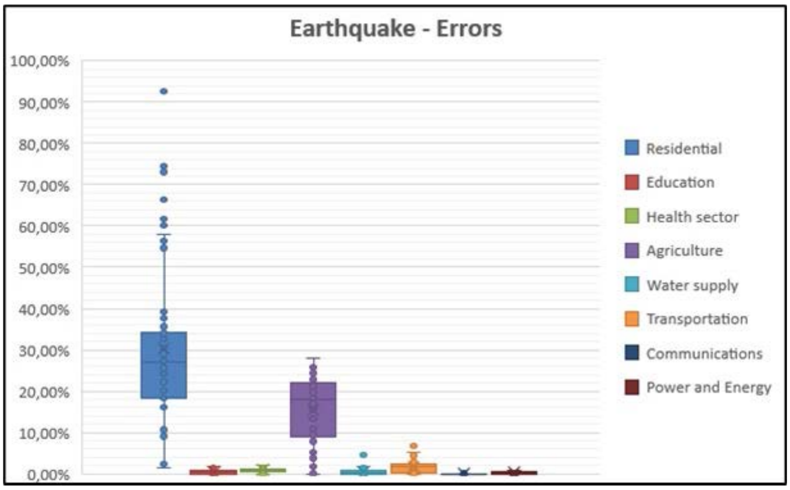




Figure 4.16: Errors on prediction

Enhancing the description of the event and increasing the number of past events result in a more accurate prediction of the lists of sectors affected. Indeed, the event description should encompass specific information regarding the hazard, including the intensity measure that characterizes the event. Additionally, it should account for the vulnerability of various assets within the sectors and the exposure represented by the goods surrounding the event location.

## 4.6 Phase 5: Indirect Impacts

The indirect impact phase of the methodology involves assessing cascade effects based on the initial group of directly impacted sectors. In this phase, the focus shifts from the primary impact of the event to understanding the secondary consequences across various sectors.

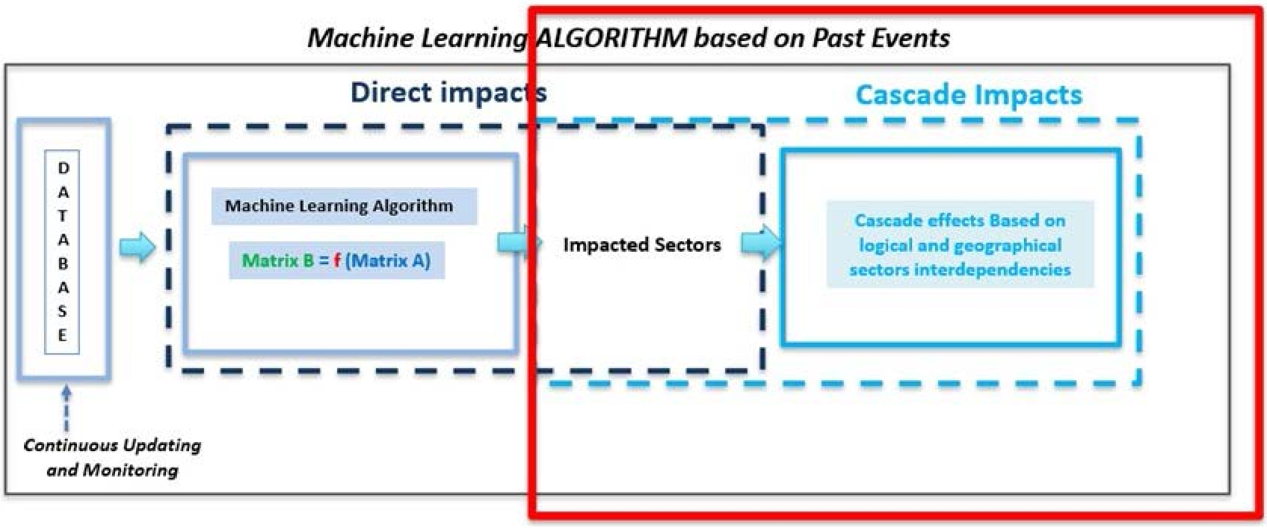



Figure 4.17: Phase 5 – Cascading impacts

The first step of this phase is to determine the correlations between the sub-sectors. Considering the types of dependencies defined in chapter 2.5, in Table 4.8 the correlations between sectors is provided considering a *logical* dependency (Rinaldi, 2001; Rehak, 2008)

Table 4.8: Correlative Analysis of Identified CI sectors (adapted from Rehak, 2008)

| | Power and Energy | Transportation | Water supply network | Communications | Health sector | Agriculture | Education | Residential Buildings | Deaths | Infjured |
|---|---|---|---|---|---|---|---|---|---|---|
| Power and Energy | x | 1 | 1 | 1 | 1 | 0 | 1 | 1 | 0 | 0 |
| Transportation | 0 | x | 1 | 0 | 1 | 0 | 1 | 1 | 0 | 0 |
| Water supply network | 1 | 0 | x | 0 | 1 | 1 | 0 | 0 | 0 | 0 |
| Communications | 0 | 0 | 0 | x | 1 | 0 | 0 | 0 | 0 | 0 |
| Health sector | 0 | 0 | 0 | 0 | x | 0 | 0 | 0 | 1 | 1 |
| Agriculture | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 |

| | | | | | | | | | | |
|---|---|---|---|---|---|---|---|---|---|---|
| **Education** | 0 | 0 | 0 | 0 | 0 | 0 | x | 0 | 0 | 0 |
| **Residential Buildings** | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 |

The correlation is always determined by the direction of the line →column

- x: Sub-sector failure can be caused internally;
- 1: Sub-sector Si can cause the failure of sub-sector Sj;
- 0: Sub-sector Si cannot cause the failure of sub-sector Sj.

It appears that power supply is the most frequent originator. The education and residential sectors are mainly vulnerable systems, acting then as impacted systems, more than originating system.
In the following example, a scenario is reported where the first group of sectors directly impacted are transportation, power and energy. Then the cascading impacts emanating from these two sectors across all sectors are interpreted.

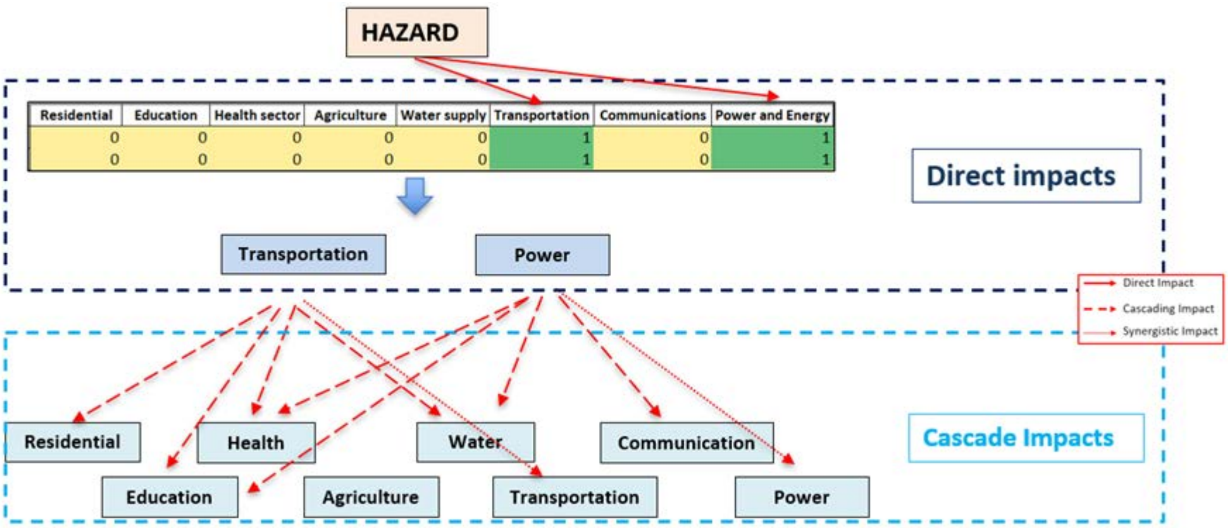



Figure 4.18:Complete example of the methodology

# 5 RESULTS FOR THE SELECTED MULTI-HAZARD PAIRS

From the 12 pairs of multi-hazard events identified in the four study regions, the MEDiate project has chosen four specific pairs for in-depth investigation. These investigations aim to contribute to the development of the project's Decision Support System (DSS). The following are the four hazard pairs along with their corresponding multi-hazard type:

1. Oslo – Compound coastal and riverine flood events
2. Nice – Extreme heat and drought events
3. Essex – Extreme wind and rainfall events
4. Múlaþing – Heavy rain and landslide events

To validate the methodology developed for Task 2.3, we asked any information or datasets containing details about historical events that have occurred in the testbeds and/or in the affiliated area. The required data were:

1. Type of hazard

2. Date of the event occurrence
3. Location of the starting point
4. Location of impact with critical elements or infrastructure
5. Magnitude of the event.
6. Description of impacts

The most needed information was regarding points 1, 3, 4, and 5.

The following chapters describe the data collected for each case study on historical events and their related direct and cascading impacts. The data was collected with the support of some partners and through extensive historical data research.

## 5.1 Oslo testbed Compound coastal and riverine flood events

### 5.1.1 Data collection

#### *5.1.1.1 Impact from historical events*

The partners assisting the Oslo testbed supported Task 2.3 with some websites. In detail, Norway has a natural disaster event website https://naturhendelser.varsom.no/.

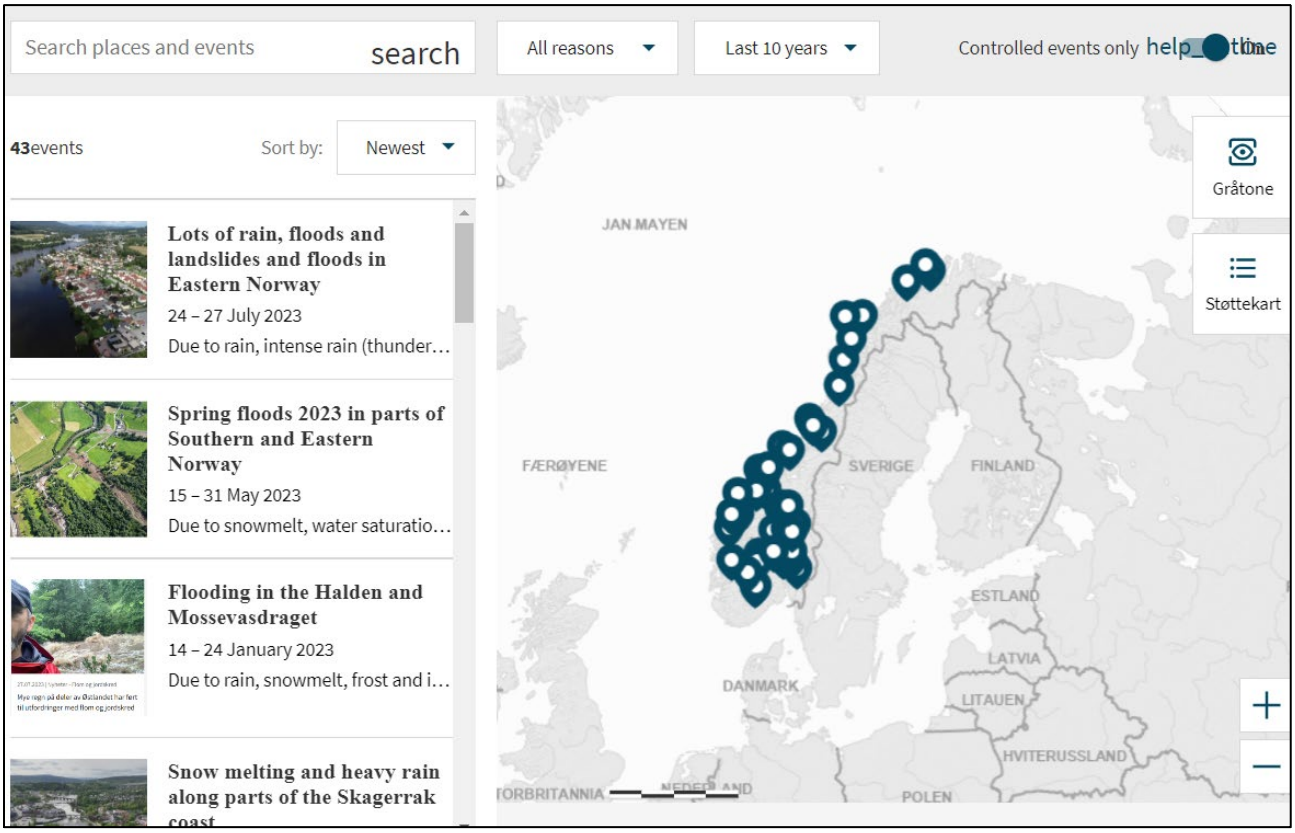



Figure 5.1: Norwegian natural disaster event website (source https://naturhendelser.varsom.no/)

The website provides information about the impacts of natural hazards in Norway. The information is provided in a variety of formats, including:

- **Qualitative description**: The website provides descriptions of the impacts of natural hazards. These descriptions include information on the types of damage that can be caused by natural hazards, as well as the number of people and properties that are at risk.
- **Maps**: The website provides maps that show the areas that are at risk of different types of natural hazards.
- **Images**: The website provides images of the impacts of natural hazards. These images can be used to help the user visualize the damage that can be caused by natural hazards.

The information on the website is updated regularly to ensure that it is accurate and up-to-date. The website is a valuable resource. Here are some additional details about the information on impacts provided on the website:

- **Flood warnings**: the warnings are based on factors such as rainfall, snowmelt, and river levels. The warnings also include information on the potential impacts of flooding, such as road closures, power outages, and evacuations.
- **Flood maps**: for different parts of Norway. The maps show the areas that are at risk of flooding at different water levels. The maps also include information on the potential impacts of flooding in different areas, such as the depth of flooding and the types of damage that could occur.
- **Information about other natural hazards**: the website also provides information about other natural hazards, such as landslides, avalanches, and wildfires.

Additional material were provided by the partners supporting the Oslo case study from the following sources:

1. Xgeo. National Norwegian database of meteorological and climate data - https://www.xgeo.no/ (Grid data)
2. SeNorge https://www.senorge.no/ (Grid data)
3. Grid based API service for Xgeo https://api.nve.no/doc/gridtimeseries-data-gts/ (Grid data)
4. Hydrological data API by weather station https://hydapi.nve.no/UserDocumentation/ (Station data)
5. Download from weather stations https://seklima.met.no/observations/ (Station data)
6. Hydrological data by hydrological station https://seriekart.nve.no/ (Norwegian only) (Station data)
7. Modulated urban floodways https://od2.pbe.oslo.kommune.no/xkart/kommuneplaninnsyn/ (Area raster)

The sources provide this information:

- Gjerdrum quick clay slide in Ask municipality on 30.12.2020, reference position UTM33 X:279460 Y:6665226 (Source 1, 2, 3, 5);
- Urban flood on Karl Johan on 02.06.2013 (Source 4, 5, 6, 7);
- Torrential rain event (Lille Hans) on 27.08.2023 (initiated late on the 26.08.23, ~h20.00), (Source 4, 5, 6, 7)

Table 5.1 summarizes the key events of Oslo's floods highlighting direct and cascading impacts.

Table 5.1: Cascading impacts from flood in Oslo

| DATE | EVENT DESCRIPTION | DIECT IMPACTS | CASCADING IMPACTS | REFERENCE |
|---|---|---|---|---|
| Feb 1987 | Rapid snowmelt combined with heavy rain caused flooding in the Akerselva River. | Property damage, infrastructure disruption | Disruptions to transportation networks (roads, bridges) | Aftenposten https://www.aftenposten.no/ (1987-02-18) |
| Aug 2000 | Intense rainfall overwhelmed the city's drainage system, causing widespread street flooding. | Transportation disruptions, business closures | Increased risk of accidents, economic losses | Dagbladet (2000-08-01) |
| Jan 2010 | Thaw and heavy rain caused the Lake Maridalsvannet | Risk of dam overflow, Psychological | Potential infrastructure | NRK https://www.nrk.no/ |

| | | | | |
|---|---|---|---|---|
| | water level to rise significantly. | stress, displacement | failure (dam breach) | (2010-01-05) |
| Nov 2011 | Storm "Berit" brought strong winds and heavy precipitation, causing flooding in coastal areas. | Building damage | Disruption of power grids, potential contamination of water supplies | Aftenposten [https://www.aftenposten.no/](https://www.aftenposten.no/) (2011-11-21) |

#### *5.1.1.2 Exposure*

The following information were shared for the spatial characterization of the element exposed to natural hazards:

- Area of interest
- Land use polygon
- Population
- Building
- Income
- Household
- Road network
- Power supply
- School
- Hospital

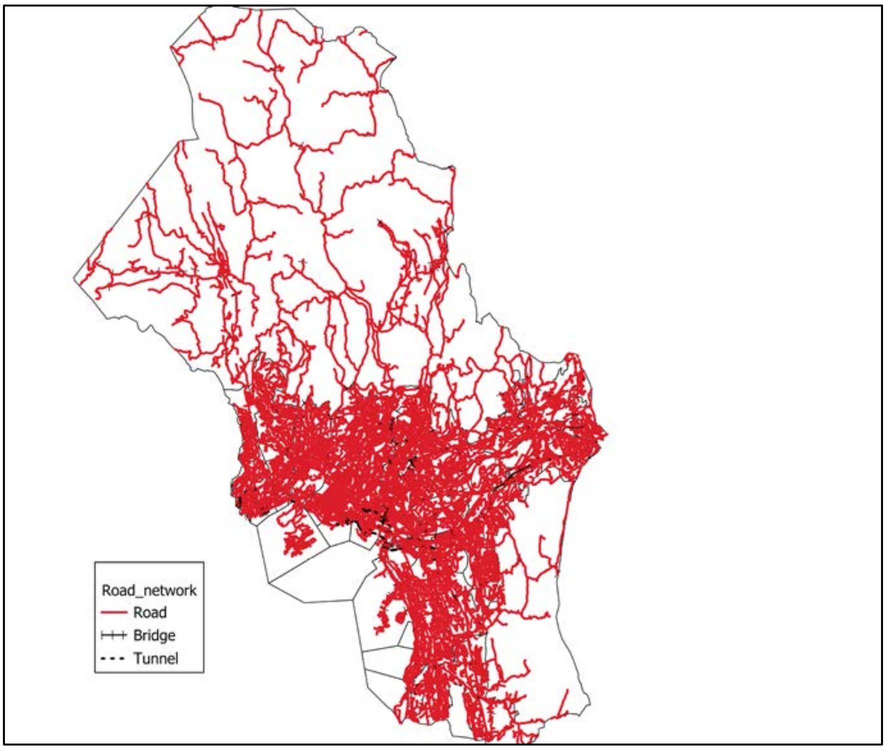



Figure 5.2: Oslo – road network

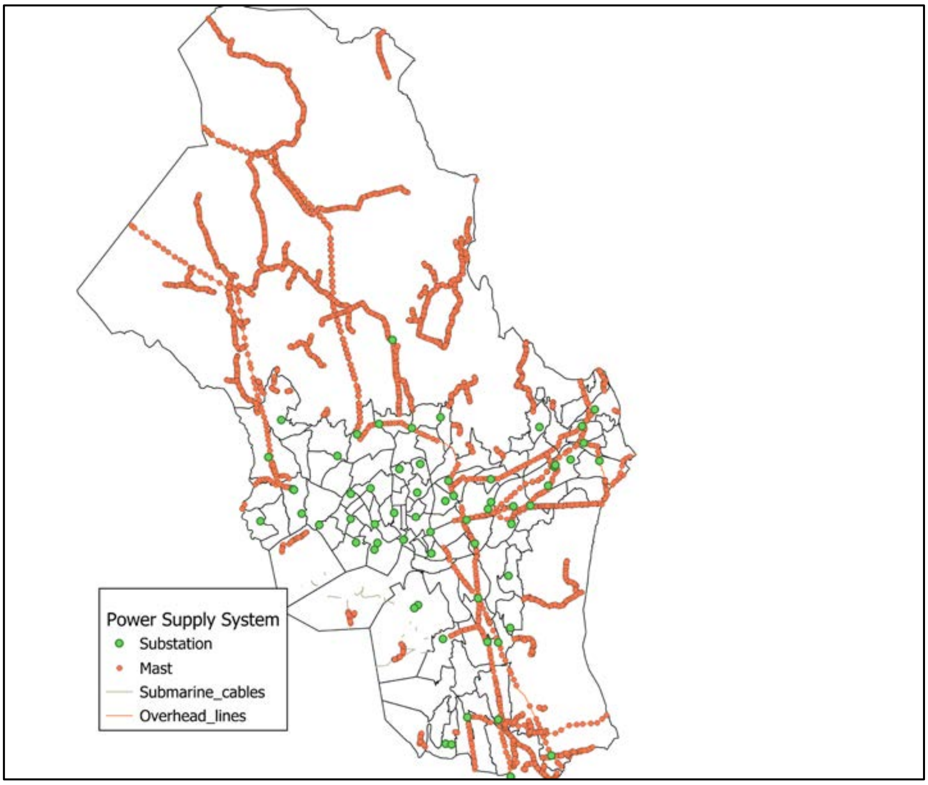


Figure 5.3: Oslo – Power supply system

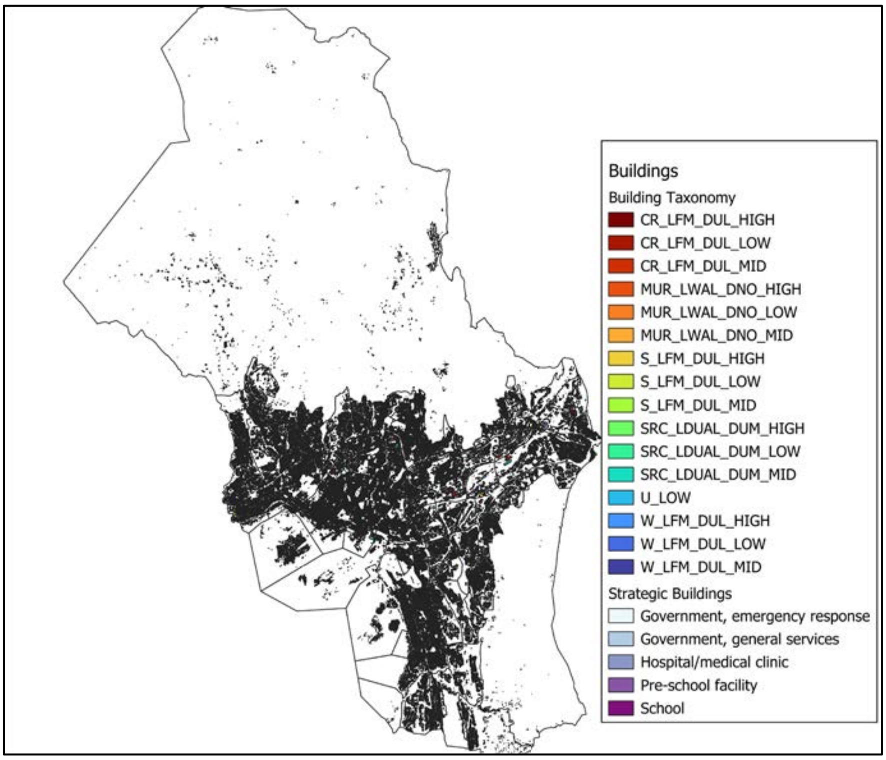


Figure 5.4: Oslo – buildings

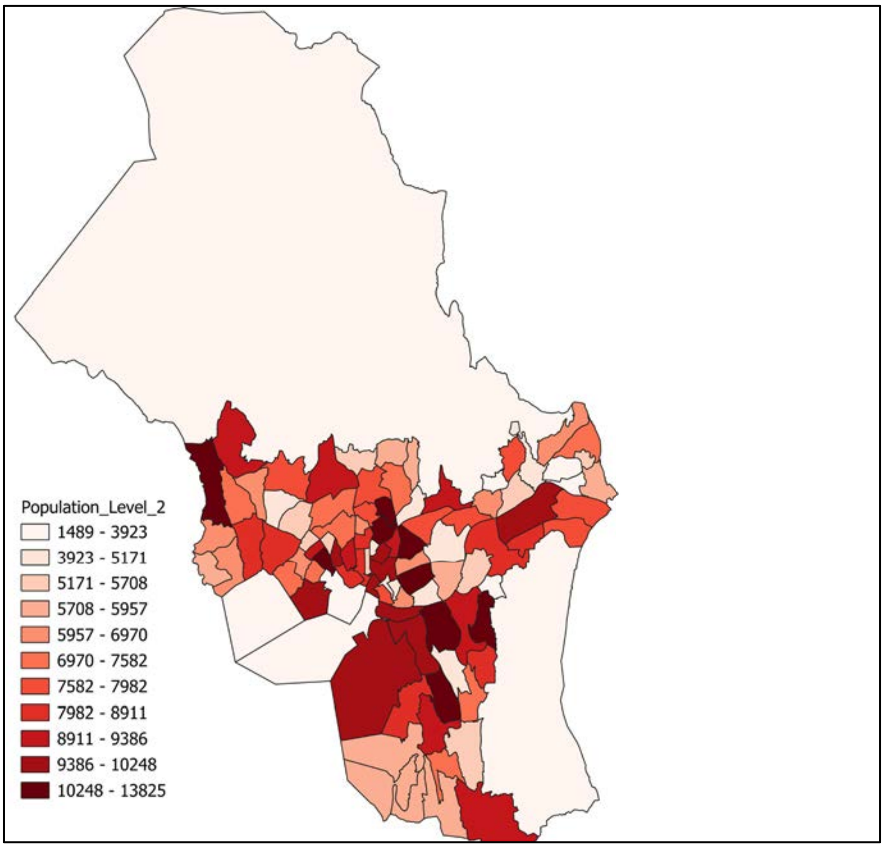



Figure 5.5: Oslo – Population

## 5.2 Nice testbed: Extreme heat and drought

### 5.2.1 Data

#### *5.2.1.1 Impact from historical events*

Table 5.2 summarizes the key events in Nice from extreme heat and drought highlighting direct and cascading impacts.

Table 5.2: Cascading impacts from Extreme heat and drought in Nice

| DATE | EVENT DESCRIPTION | DIECT IMPACTS | CASCADING IMPACTS | REFERENCE |
|---|---|---|---|---|
| Summer 1976 | Prolonged hot, dry weather with above-average temperatures. | Increased water demand | Increased stress on agriculture and ecosystems | Météo-France historical data |
| Summer 2003 | Heatwave with record-breaking temperatures. | increased air pollution, health problems, mortality increase | Increased strain on healthcare systems, disruption to outdoor activities | Heatwave in France August 2003: https://en.wikipedia.org/wiki/2003_European_heat_wave |

| | | | | |
|---|---|---|---|---|
| Summer 2019 | Drought conditions with limited rainfall and high temperatures. | Water scarcity, restrictions on use | Reduced agricultural yields, impact on tourism (e.g., water restrictions affecting beaches) | Drought in France 2019 |

#### *5.2.1.2 Exposure*

The following information were shared for the spatial characterization of the element exposed to natural hazards:

- Area of interest
- Building stock
- DEM
- Power network
- Road network
- Soil classes
- Land use.

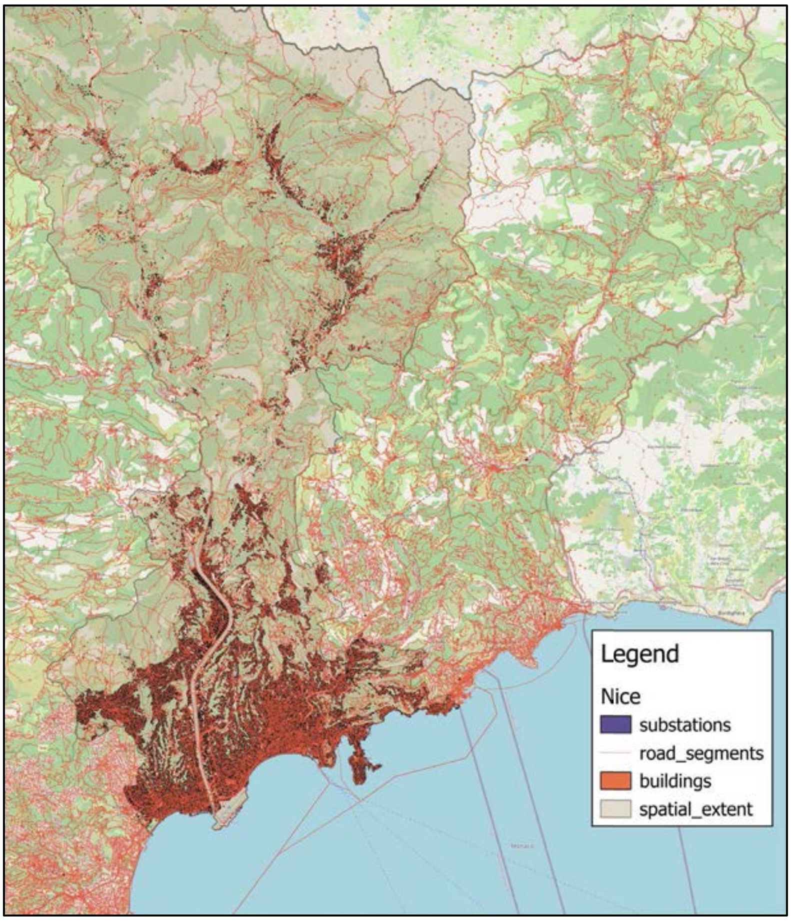



Figure 5.6: Nice – Exposure

## 5.3 Essex testbed: Extreme wind and rainfall

### 5.3.1 Data

#### *5.3.1.1 Impact from historical events*

Table 5.3 summarizes the key events in Essex from extreme heat and drought highlighting direct and cascading impacts.

Table 5.3: Cascading impacts from Extreme wind and rainfall in Essex

| DATE | EVENT DESCRIPTION | DIECT IMPACTS | CASCADING IMPACTS | REFERENCE |
|---|---|---|---|---|
| Jan 1978 | Severe storm with high winds and heavy rain. | Power outages, property damage (fallen trees, debris) | Disruptions to transportation (roads, bridges) | Essex Chronicle historical archives (if available online) |
| Oct 1987 | Great Storm of 1987: Strong winds and heavy rainfall causing widespread damage. | Widespread power outages, property damage (buildings, roofs) | Disruptions to transportation and communication networks, economic losses | BBC - On This Day: http://news.bbc.co.uk/onthisday/hi/years/1987/default.stm |
| Dec 1999 | Low-pressure system bringing high winds and coastal flooding. | Damage to coastal infrastructure, property damage | Disruptions to transportation (flooded roads), potential contamination of water supplies | Environment Agency flood reports |

#### *5.3.1.2 Exposure*

The following information were shared for the spatial characterization of the element exposed to natural hazards:

- Castle area
- Major roads
- Greenspace sites
- Power network
- Population

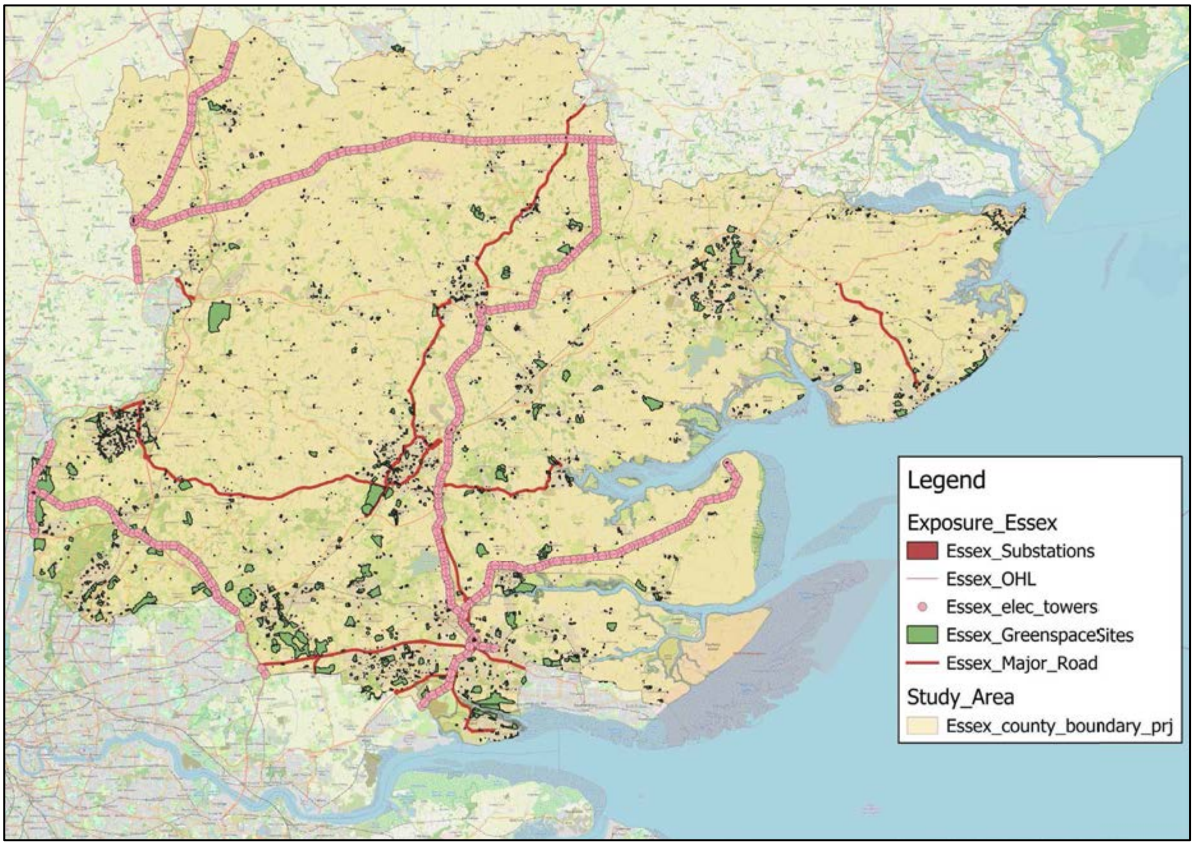



Figure 5.7: Essex – Exposure

## 5.4 Múlaþing testbed: heavy rain and landslides

### 5.4.1 Data

#### *5.4.1.1 Impact from historical events*

The partners assisting the Múlaþing testbed supported Task 2.3 with some information. Despite the effort, the data is not useful given the lack of intensity measure for the selected hazard pairing. Figure 5.6 shows the representation of the shared data related to the landslides.

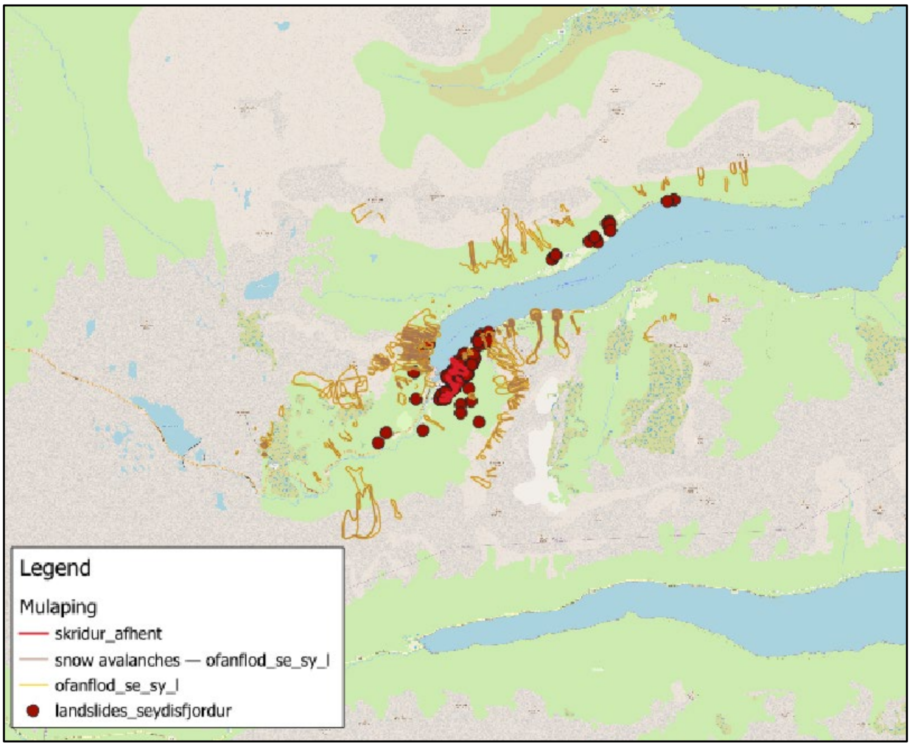



Figure 5.8: Múlaþing – Historical data

Table 5.4 summarizes the key events in Múlaþing from heavy rain and landslides highlighting direct impacts provided by IMO.

Table 5.4: Direct impacts from heavy rain and landslides in Múlaþing

| DATE | DESCRIPTION OF THE DIRECT IMPACT |
|---|---|
| 2020-12-15 15:21:00.000000 | The landslide wreaked havoc on gardens and filled the basement on East Road 40 (Broad) with mud. The landslide also blocked the road through East Avenue and filled the car park at the gas station with mud. |
| 2020-12-15 15:21:00.000000 | The landslide wreaked havoc on gardens and filled the basement on East Road 40 (Broad) with mud. The landslide also blocked the road through East Avenue and filled the car park at the gas station with mud. |
| 2020-12-15 15:21:00.000000 | The landslide wreaked havoc on gardens and filled the basement on East Road 40 (Broad) with mud. The landslide also blocked the road through East Avenue and filled the car park at the gas station with mud. |
| 2020-12-15 22:39:00.000000 | The landslide crossed the landslide that fell earlier in the day, adding to the problem that had already occurred. |
| 2020-12-18 18:00: | |
| 2020-12-16 21:24:00.000000 | A thin layer of landslide material went down the street toward Mule Road. The landslide didn't block the street, it was still passable even though the neighborhood had been evacuated. |
| 2020-12-18 23:14:00 | |
| 2020-12-17 09:00:00. | |
| 2020-12-15 06:00:00 | |
| 2020-12-18 12:10:00. | |

| | |
|---|---|
| 2020-12-18 12:10:00 | |
| 2020-12-18 14:56:00.000000 | The landslide took about 10 houses in Budareyri and damaged everything in its path. It is a shame that no one was killed or injured in this incident. Rescue teams were in a car on the edge of the landslide and barely escaped. |
| 2020-12-19 00:00:00. | |
| 2020-12-15 16:00:00.000000 | The landslide went through the backyard of Bottom Hill 35, causing damage to the park. |
| 2020-12-18 13:30:00 | |
| 2020-12-15 19:40:00.000000 | Landslide material went down into the backyard on Bottom Hill 35 |
| 2020-12-15 19:40:00.000000 | Landslide material went down into the backyard on Bottom Hill 36 |
| 2020-12-14 20:00:00 | |
| 2020-12-15 04:00:00 | |
| 2020-12-16 10:00:00. | |
| 2020-12-16 10:00:00. | |
| 2020-12-17 22:00:00.000000 | The landslide went through the backyard on Bottom Hills 33 and 35, causing damage to the park |
| 2020-12-17 22:00:00.000000 | The landslide went through the backyard on Bottom Hills 33 and 35, causing damage to the park |
| 2020-12-19 03:00:00.000000 | A landslide went into the backyard of an apartment building standing at Bottom Hill 15, also piled landslide material against the wall of a house at Bottom Hill 19 and found its way into the garage. |
| 2020-12-16 10:00:00 | |
| 2020-12-16 10:00:00 | |
| 2020-12-18 03:15:00.000000 | The landslide caused extensive damage, including taking the apartment building Breiðablik from the foundation and floating it down the street. The house was completely destroyed. A lot of mud accumulated on the road around East Road and in the car park at the gas station. |
| 2020-12-18 03:15:00.000000 | The landslide caused extensive damage, including taking the apartment building Breiðablik from the foundation and floating it down the street. The house was completely destroyed. A lot of mud accumulated on the road around East Road and in the car park at the gas station. |
| 2020-12-18 03:15:00.000000 | The landslide caused extensive damage, including taking the apartment building Breiðablik from the foundation and floating it down the street. The house was completely destroyed. A lot of mud accumulated on the road around East Road and in the car park at the gas station. |
| 2020-12-18 03:15:00.000000 | The landslide caused extensive damage, including taking the apartment building Breiðablik from the foundation and floating it down the street. The house was completely destroyed. A lot of mud accumulated on the road around East Road and in the car park at the gas station. |
| 2020-12-18 14:56:00.000000 | The landslide took about 10 houses in Budareyri and damaged everything in its path. It is a shame that no one was killed or injured in this incident. Rescue teams were in a car on the edge of the landslide and barely escaped. |
| 2020-12-18 14:56:00.000000 | The landslide took about 10 houses in Budareyri and damaged everything in its path. It is a shame that no one was killed or injured in this incident. Rescue teams were in a car on the edge of the landslide and barely escaped. |
| 2020-12-18 14:56:00.000000 | The landslide took about 10 houses in Budareyri and damaged everything in its path. It is a shame that no one was killed or injured in this incident. Rescue teams were in a car on the edge of the landslide and barely escaped. |

| | |
|---|---|
| 2020-12-18 14:56:00.000000 | The landslide took about 10 houses in Budareyri and damaged everything in its path. It is a shame that no one was killed or injured in this incident. Rescue teams were in a car on the edge of the landslide and barely escaped. |
| 2020-12-18 14:56:00.000000 | The landslide took about 10 houses in Budareyri and damaged everything in its path. It is a shame that no one was killed or injured in this incident. Rescue teams were in a car on the edge of the landslide and barely escaped. |
| 2020-12-19 00:00:00. | |
| 2020-12-15 15:21:00.000000 | The landslide wreaked havoc on gardens and filled the basement on East Road 40 (Broad) with mud. The landslide also blocked the road through East Avenue and filled the car park at the gas station with mud. |

#### *5.4.1.2 Exposure*

The following information were shared for the spatial characterization of the element exposed to natural hazards:

- Bridges
- Major roads
- Buildings

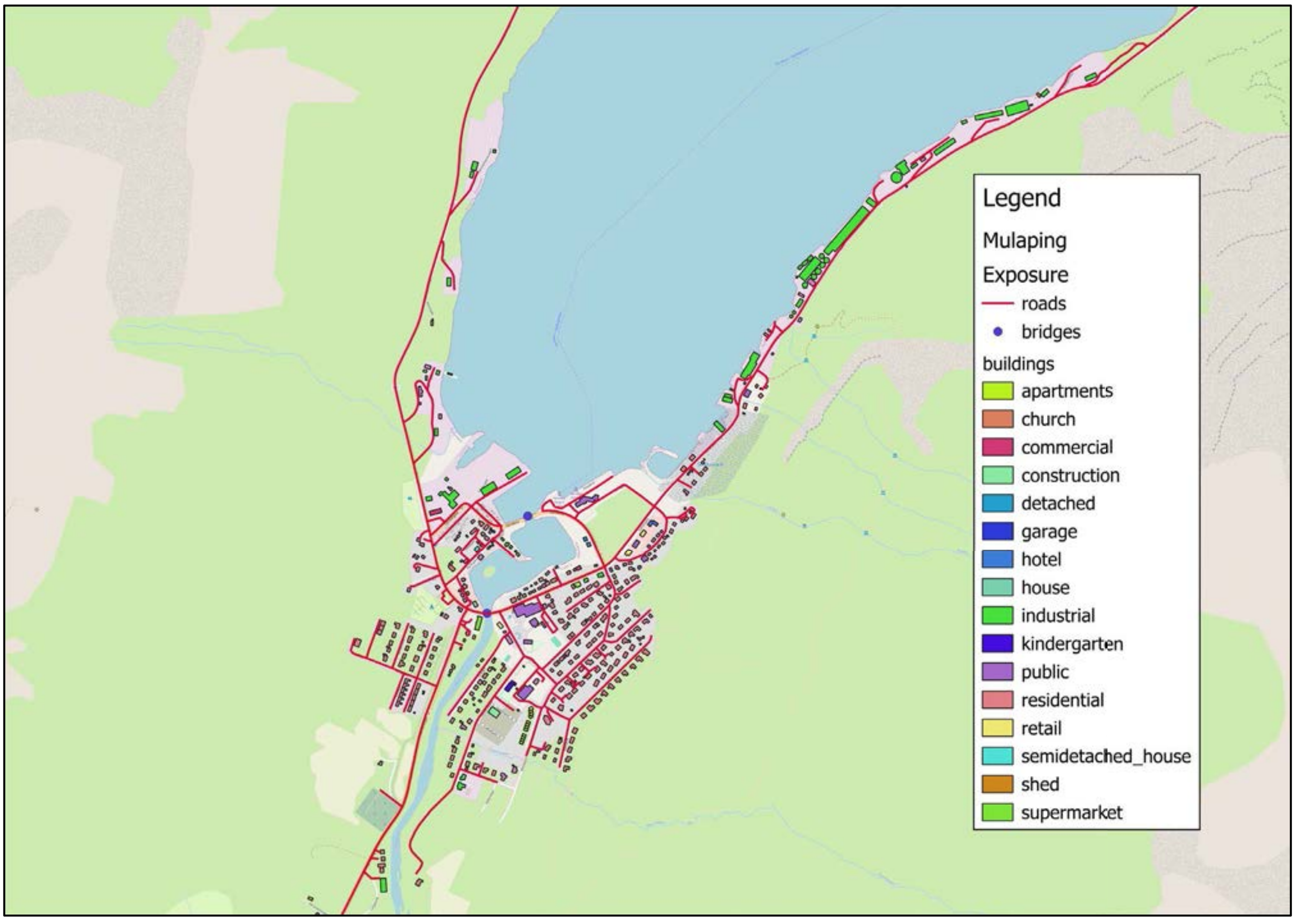



Figure 5.9: Múlaþing – Exposure

## 5.5 Identifying direct impacts and cascading impacts for each testbed

In this chapter, we will demonstrate how machine learning can be applied to historical data for each case study, highlighting how it can identify patterns and trends that would otherwise be difficult to discern. By leveraging machine learning algorithms, we can extract valuable insights from the data and use them to make informed decisions and predictions.

Table 5.5 delves into the direct and cascading effects of the chosen hazards. It leverages insights gleaned from both the collected historical data and the analysis conducted using machine learning techniques.

Table 5.5: Cascading impacts from the selected hazards

| HAZARD | DIRECT IMPACTS | POTENTIAL CASCADING IMPACT | ADDITIONAL NOTES ON CASCADING IMPACTS |
|---|---|---|---|
| **Flood** | • **Infrastructure Damage:** Buildings, roads, bridges, power grids, communication networks<br>• **Loss of Life and Displacement:** Evacuation needs, injuries, fatalities<br>• **Contamination of Water Supplies:** Sewage overflow, disruption of water treatment facilities<br>• **Disruption of Services:** Transportation, healthcare, emergency response<br>• **Economic Losses:** Agriculture, businesses, tourism<br>• **Environmental Damage:** Erosion, loss of habitat, spread of pollutants | • Disrupted transportation routes isolate communities, hindering emergency response (**Delayed medical care, increased fatalities**)<br>• Contaminated water supplies lead to outbreaks of waterborne diseases (**Increased hospitalizations, long-term health problems**)<br>• Damaged power grids cause outages at hospitals, disrupting medical care (**Loss of critical medical equipment function, additional fatalities**) | Cascading impacts vary depending on flood severity, duration, and preparedness levels. Floodwaters can disrupt transportation routes, isolating communities and hindering emergency response efforts. Contaminated water supplies can lead to outbreaks of waterborne diseases. Economic losses can occur due to damaged infrastructure, agricultural losses, and business closures. |
| **Drought** | • **Water Scarcity:** Reduced water availability for drinking, agriculture, and industry<br>• **Agricultural Losses:** Crop failure, soil erosion<br>• **Power Outages:** Reliance on hydroelectric power<br>• **Economic Impacts:** Reduced agricultural production, job losses in affected sectors<br>• **Social Impacts:** Food insecurity, malnutrition, population displacement | • Reduced water availability for irrigation leads to crop failure, impacting food security (**Increased food prices, malnutrition**)<br>• Hydroelectric power plants may not function at full capacity due to low water levels, leading to power outages (**Disruptions to critical services, economic losses**) | Droughts can have a significant impact on food security, particularly in regions heavily reliant on agriculture. Reduced water availability can lead to competition for resources and social tensions. |
| **Landslide** | • **Loss of Life and Property Damage:** Buildings, roads, and infrastructure<br>• **Disruption of Transportation and Communication Networks:** Blocked roads and bridges | • Blocked roads and bridges hinder emergency response efforts, delaying search and rescue operations (**Increased fatalities, delayed medical care**) | Landslides can have a devastating impact on communities, causing fatalities, destroying homes and infrastructure, and isolating areas. Disruptions to transportation networks can hinder emergency response efforts and make it |

| | | | |
|---|---|---|---|
| | • **Damage to Utilities:** Power lines, water pipes<br>• **Environmental Damage:** Erosion, sedimentation, disruption of natural habitats<br>• **Economic Losses:** Disruption of businesses and tourism | • Damaged power lines and water pipes disrupt essential services, impacting livelihoods (**Loss of income, business closures**)<br>• Disruptions to transportation networks isolate communities, hindering access to essential supplies and services (**Food shortages, increased vulnerability**) | difficult to deliver aid. Landslides can also trigger secondary hazards such as floods due to blocked waterways. |

Next, we ensured the information was relevant to each case study by factoring in the critical infrastructure present within the study area, thanks to the exposure information collected in the previous chapters.
Table 5.6 shows the direct impacts determined with the machine learning approach. This was the starting point of the cascading impact assessment. It is important to underline that, considering the type of dependencies and the scheme of propagation shown in figure 4.2, the propagation starts only when the so-called originating systems are hitted by an hazard:

- Power and energy
- Communication
- Transportation
- Water supply sector.

Table 5.6: Direct impacts from the selected hazards – ML outputs

| Event | Region | Houses Damaged | Education | Health sector | Agriculture | Water supply | Transportation | Communications | Power and Energy |
|---|---|---|---|---|---|---|---|---|---|
| Compound coastal and riverine flood | Oslo | 0,2842 | 0 | 0,0006 | 0,3253 | 0,1135 | 0,2723 | 0 | 1,0000 |
| Extreme heat and drought events | Nice | 0 | 0 | 0 | 0,2555 | 0,0753 | 0 | 0 | 1 |
| Extreme wind and rainfall events | Essex | 0,3228 | 0,0479 | 0,0207 | 0,6149 | 0,2810 | 0,2833 | 0,0861 | 0,7900 |
| Heavy rain and landslide | Mulaping | 1 | 0,4853 | 0,1394 | 1 | 0 | 1 | 1 | 0,8318 |

Figures 5.10, 5.11, 5.12 and 5.13 present the results for each testbed.

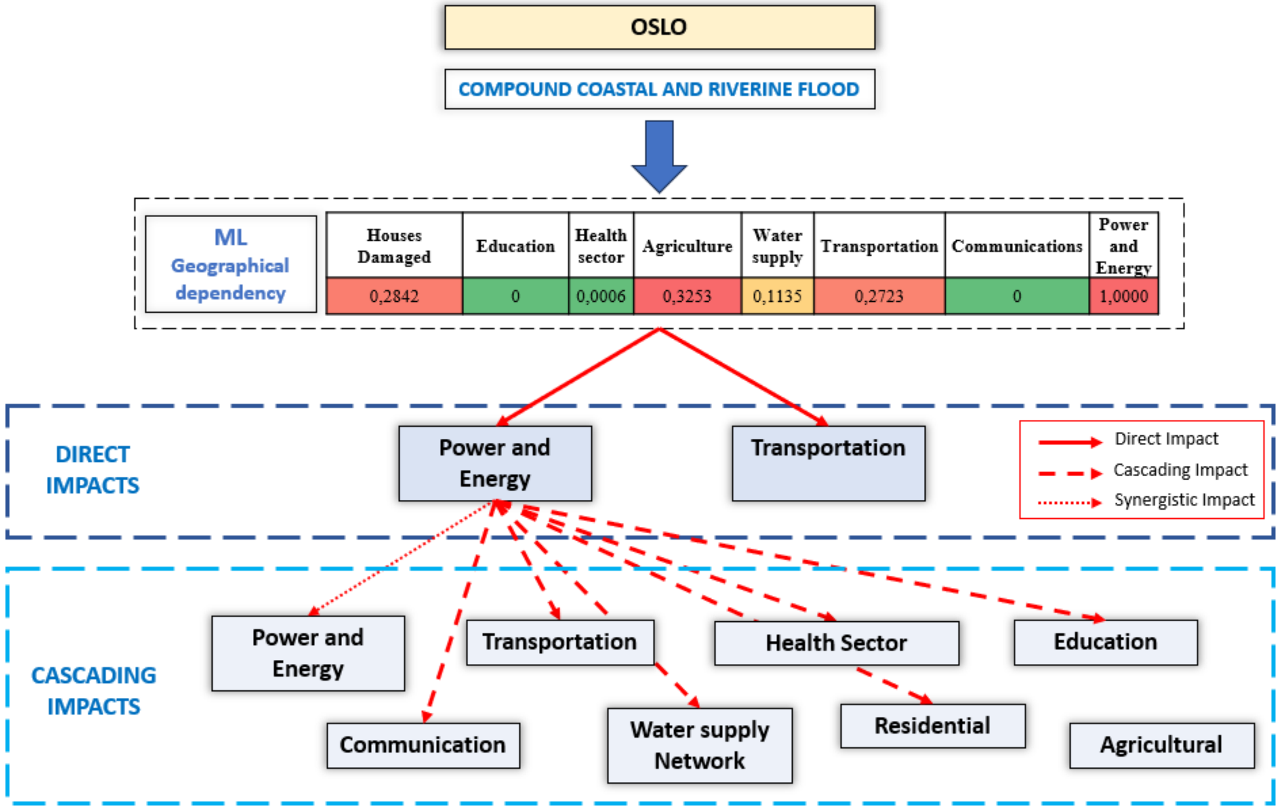



Figure 5.10: Oslo – Assessment of the primary cascading impacts

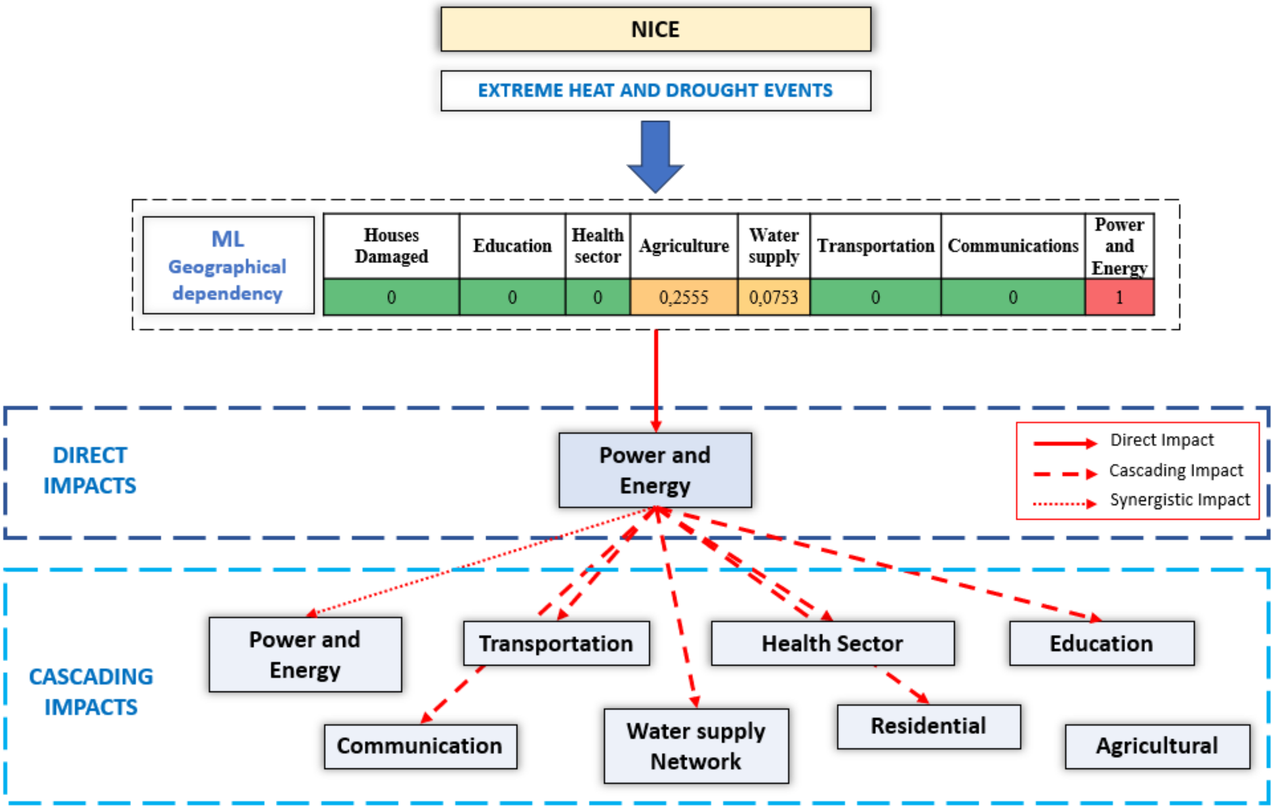



Figure 5.11: Nice – Assessment of the primary cascading impacts

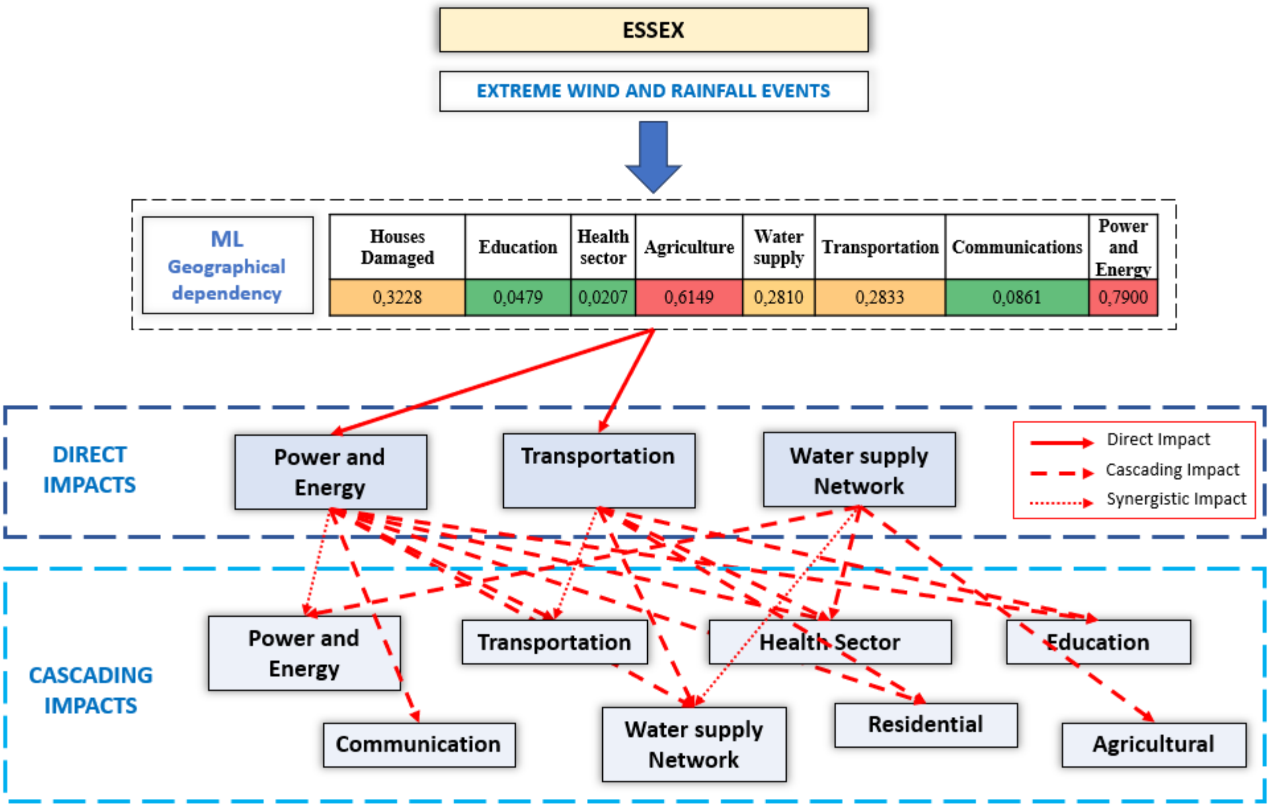



Figure 5.12: Essex – Assessment of the primary cascading impacts

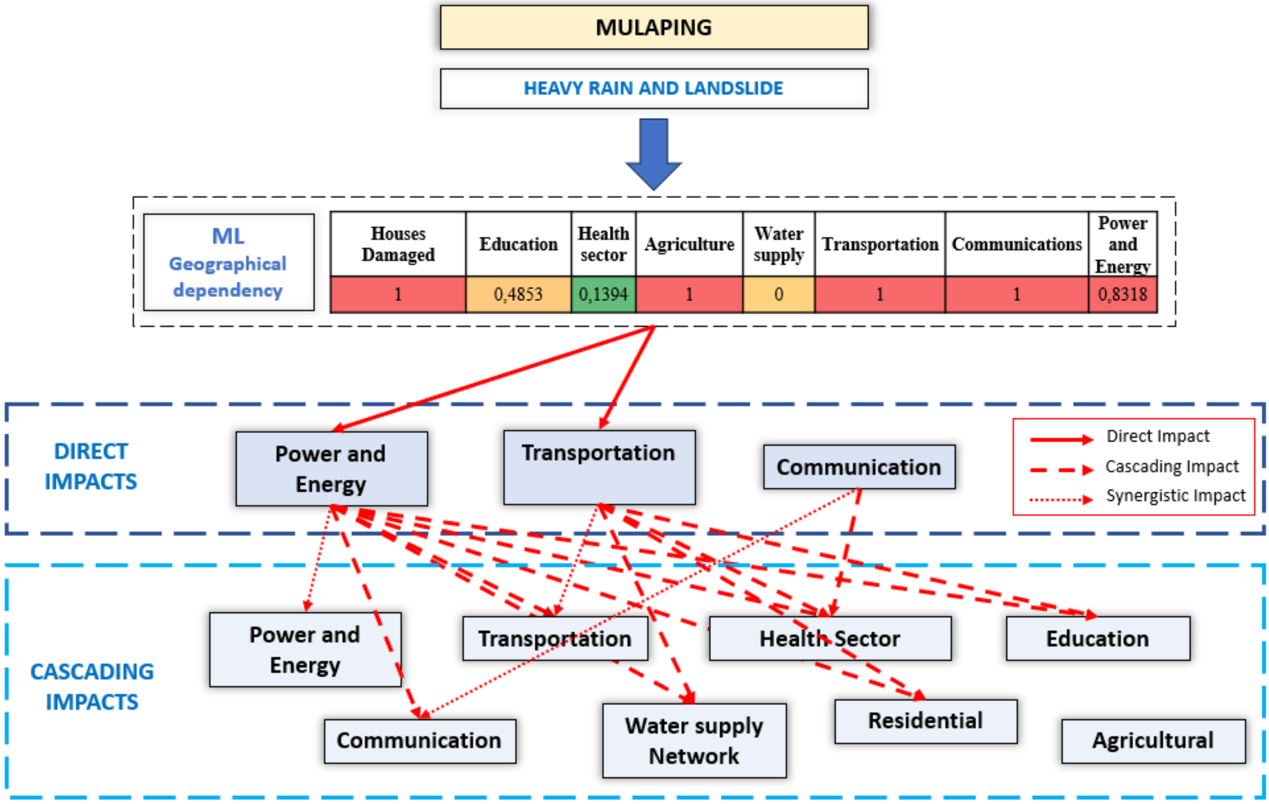



Figure 5.13: Mulaping – Assessment of the primary cascading impacts

It appears that power supply is the most frequent originator. The education and residential sectors are mainly vulnerable systems, acting then as impacted systems, more than originating system.

Despite the available data are not sufficient for a perfect event description, the obtained results are consistent with expectations.

Upon reviewing the comparison between the actual impacts on sectors and the predictions made by the algorithm, it can be asserted that there are some notable achievements.

# 6 DISCUSSION

The methodology developed in task Task 2.3, grounded in machine learning techniques, has the potential to enhance decision-making processes aimed at addressing the challenges associated with cascading impacts. The main point of this discussion concerns the methodology itself, as the model can delineate impacted sectors based on hazards, only considering their spatial proximity and surrounding context. One key aspect highlighted by the task is the non-availability of a sufficient number of historical event data in the case studies, which is essential for a machine learning-based methodology.
This shortage necessitated the development of a method that extracts data from global databases, albeit validated only within the case studies. However, the results didn't meet expectations primarily because the initial database wasn't extensive enough for robust training. Given the multitude of variables involved but the limited scenarios available, the reliability of predictions faces some challenges, especially regarding differentiating impacts based on magnitude.
Nevertheless, despite these challenges, the developed methodology has demonstrated functionality and yielded satisfactory results during validation. While this validates its potential for application in other European contexts, it also underlines the importance of greater information collection by those dealing with these natural hazards at the local level.
This task has indeed played a dual role in highlighting this widespread lack of adequate data collection, which hopefully will change in the future. The involvement of stakeholders in the MEDiate project as partners and actors of the same project indeed represents an opportunity to improve this aspect, asking that those dealing with natural hazards at the local level collect detailed information on events, in terms of event impact location and event magnitude.

Although the Task 2.3 concludes at M18, the model remains valid and functional. In the event that new scenarios become available from stakeholders in the testbeds, the model can be rerun, and the results updated accordingly. This iterative process ensures the continued relevance and efficacy of the developed methodology in addressing the evolving challenges of cascading impacts.

The inclusion of additional information about the event enhances the algorithm's prediction accuracy, as the understanding of the event aligns with traditional risk analyses conducted for Critical Infrastructures.

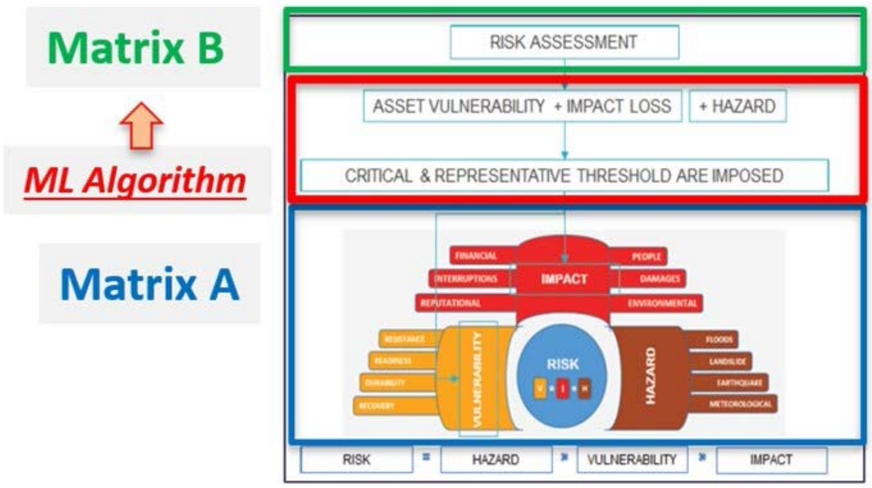



Figure 6.12: Traditional Risk Assessment for CI

The more accurately the Hazard, Vulnerability, and Exposure are described, the better results are achieved certainly. The machine learning algorithms are expected to serve as a substitute for the traditional analysis conducted across all sectors. This substitution occurs through predictions derived from past events. By leveraging historical data and training models on these events, machine learning algorithms can effectively forecast potential impacts on various sectors. This predictive capability streamlines the analysis process, providing insights into potential outcomes without the need for exhaustive sector-by-sector analysis. As a result, the reliance on historical data and algorithmic predictions enables a more efficient and scalable approach to assessing risks and planning responses to future events.

# 7 CONCLUSIONS

Task 2.3 has achieved its objectives in assessing cascading impacts resulting from multi-hazard interactions across several areas in Europe. Through the implementation of a methodology grounded in data-driven learning approaches, task 2.3 have gained comprehensive insights into the spatial and temporal evolution of these cascading effects. By leveraging historical data sources such as EM-DAT and DesInventar, task 2.3 has identified potential chain reactions of consequences, enriching our understanding of multi-sectoral impacts.
The method should be applicable for describing cascading effects among a broad variety of societal sectors and critical infrastructures
The methodology develops an impact assessment framework, coupled with the utilization of machine learning techniques, enhancing our ability to comprehend the complexities of cascading impacts.
This methodology will inform decision-making processes aimed at addressing the challenges associated with cascading impacts.

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# 9 APPENDIX

Table A.1 Critical entities identified for each sector and subsector - Directive (EU) 2022/2557 Of The European Parliament And Of The Council Of 14 December 2022

| Sectors | Subsectors | |
|---|---|---|
| Energy | Electricity | Electricity undertakings as defined in Article 2, point (57), of Directive (EU) 2019/944 of the European Parliament and of the Council ([1]), which carry out the function of 'supply' as defined in Article 2, point (12), of that Directive |
| | | Distribution system operators as defined in Article 2, point (29), of Directive (EU) 2019/944 |
| | | Transmission system operators as defined in Article 2, point (35), of Directive (EU) 2019/944 |
| | | Producers as defined in Article 2, point (38), of Directive (EU) 2019/944 |
| | | Nominated electricity market operators as defined in Article 2, point (8), of Regulation (EU) 2019/943 of the European Parliament and of the Council ([2]) |
| | | Market participants as defined in Article 2, point (25), of Regulation (EU) 2019/943 providing aggregation, demand response or energy storage services as defined in Article 2, points (18), (20) and (59), of Directive (EU) 2019/944 |
| | District heating and cooling | Operators of district heating or district cooling as defined in Article 2, point (19), of Directive (EU) 2018/2001 of the European Parliament and of the Council ([3]) |
| | Oil | Operators of oil transmission pipelines |
| | | Operators of oil production, refining and treatment facilities, storage and transmission |
| | | Central stockholding entities as defined in Article 2, point (f), of Council Directive 2009/119/EC ([4]) |
| | Gas | Supply undertakings as defined in Article 2, point (8), of Directive 2009/73/EC of the European Parliament and of the Council ([5]) |
| | | Distribution system operators as defined in Article 2, point (6), of Directive 2009/73/EC |
| | | Transmission system operators as defined in Article 2, point (4), of Directive 2009/73/EC |
| | | Storage system operators as defined in Article 2, point (10), of Directive 2009/73/EC |
| | | LNG system operators as defined in Article 2, point (12), of Directive 2009/73/EC |
| | | Natural gas undertakings as defined in Article 2, point (1), of Directive 2009/73/EC |
| | | Operators of natural gas refining and treatment facilities |
| | Hydrogen | Operators of hydrogen production, storage and transmission |
| Transport | Air | Air carriers as defined in Article 3, point (4), of Regulation (EC) No 300/2008 used for commercial purposes |

[1] Directive (EU) 2019/944 of the European Parliament and of the Council of 5 June 2019 on common rules for the internal market for electricity and amending Directive 2012/27/EU (OJ L 158, 14.6.2019, p. 125)
[2] Regulation (EU) 2019/943 of the European Parliament and of the Council of 5 June 2019 on the internal market for electricity (OJ L 158, 14.6.2019, p. 54)
[3] Directive (EU) 2018/2001 of the European Parliament and of the Council of 11 December 2018 on the promotion of the use of energy from renewable sources (OJ L 328, 21.12.2018, p. 82)
[4] Council Directive 2009/119/EC of 14 September 2009 imposing an obligation on Member States to maintain minimum stocks of crude oil and/or petroleum products (OJ L 265, 9.10.2009, p. 9)
[5] Directive 2009/73/EC of the European Parliament and of the Council of 13 July 2009 concerning common rules for the internal market in natural gas and repealing Directive 2003/55/EC (OJ L 211, 14.8.2009, p. 94)

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| | | Airport managing bodies as defined in Article 2, point (2), of Directive 2009/12/EC of the European Parliament and of the Council ([6]), airports as defined in Article 2, point (1), of that Directive, including the core airports listed in Section 2 of Annex II to Regulation (EU) No 1315/2013 of the European Parliament and of the Council ([7]), and entities operating ancillary installations contained within airports |
| | | Traffic management control operators providing air traffic control (ATC) services as defined in Article 2, point (1), of Regulation (EC) No 549/2004 of the European Parliament and of the Council ([8]) |
| | Rail | Infrastructure managers as defined in Article 3, point (2), of Directive 2012/34/EU of the European Parliament and of the Council ([9]) |
| | | Railway undertakings as defined in Article 3, point (1), of Directive 2012/34/EU and operators of service facilities as defined in Article 3, point (12), of that Directive |
| | Water | Inland, sea and coastal passenger and freight water transport companies, as defined for maritime transport in Annex I to Regulation (EC) No 725/2004, not including the individual vessels operated by those companies |
| | | Managing bodies of ports as defined in Article 3, point (1), of Directive 2005/65/EC, including their port facilities as defined in Article 2, point (11), of Regulation (EC) No 725/2004, and entities operating works and equipment contained within ports |
| | | Operators of vessel traffic services (VTS) as defined in Article 3, point (o), of Directive 2002/59/EC of the European Parliament and of the Council ([10]) |
| | Road | Road authorities as defined in Article 2, point (12), of Commission Delegated Regulation (EU) 2015/962 ([11]) responsible for traffic management control, excluding public entities for whom traffic-management or the operation of intelligent transport systems is a non-essential part of their general activity |
| | | Operators of Intelligent Transport Systems as defined in Article 4, point (1), of Directive 2010/40/EU of the European Parliament and of the Council ([12]) |
| | public transport | Public service operators as defined in Article 2, point (d), of Regulation (EC) No 1370/2007 of the European Parliament and of the Council ([13]) |

[6] Directive 2009/12/EC of the European Parliament and of the Council of 11 March 2009 on airport charges (OJ L 70, 14.3.2009, p. 11)

[7] Regulation (EU) No 1315/2013 of the European Parliament and of the Council of 11 December 2013 on Union guidelines for the development of the trans-European transport network and repealing Decision No 661/2010/EU (OJ L 348, 20.12.2013, p. 1).

[8] Regulation (EC) No 549/2004 of the European Parliament and of the Council of 10 March 2004 laying down the framework for the creation of the single European sky (the framework Regulation) (OJ L 96, 31.3.2004, p. 1)

[9] Directive 2012/34/EU of the European Parliament and of the Council of 21 November 2012 establishing a single European railway area (OJ L 343, 14.12.2012, p. 32)

[10] Directive 2002/59/EC of the European Parliament and of the Council of 27 June 2002 establishing a Community vessel traffic monitoring and information system and repealing Council Directive 93/75/EEC (OJ L 208, 5.8.2002, p. 10).

[11] Commission Delegated Regulation (EU) 2015/962 of 18 December 2014 supplementing Directive 2010/40/EU of the European Parliament and of the Council with regard to the provision of EU-wide real-time traffic information services (OJ L 157, 23.6.2015, p. 21)

[12] Directive 2010/40/EU of the European Parliament and of the Council of 7 July 2010 on the framework for the deployment of Intelligent Transport Systems in the field of road transport and for interfaces with other modes of transport (OJ L 207, 6.8.2010, p. 1)

[13] Regulation (EC) No 1370/2007 of the European Parliament and of the Council of 23 October 2007 on public passenger transport services by rail and by road and repealing Council Regulations (EEC) Nos 1191/69 and 1107/70 (OJ L 315, 3.12.2007, p. 1)

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|---|---|---|
| Banking | | Credit institutions as defined in Article 4, point (1), of Regulation (EU) No 575/2013 |
| Financial market infrastructure | | Operators of trading venues as defined in Article 4, point (24), of Directive 2014/65/EU |
| | | Central counterparties (CCPs) as defined in Article 2, point (1), of Regulation (EU) No 648/2012 |
| Health | | Healthcare providers as defined in Article 3, point (g), of Directive 2011/24/EU of the European Parliament and of the Council ([14]) |
| | | EU reference laboratories as referred to in Article 15 of Regulation (EU) 2022/2371 of the European Parliament and of the Council ([15]) |
| | | Entities carrying out research and development activities of medicinal products as defined in Article 1, point (2), of Directive 2001/83/EC of the European Parliament and of the Council ([16]) |
| | | Entities manufacturing basic pharmaceutical products and pharmaceutical preparations as referred to in Section C division 21 of NACE Rev. 2 |
| | | Entities manufacturing medical devices considered as critical during a public health emergency (‘public health emergency critical devices list’) within the meaning of Article 22 of Regulation (EU) 2022/123 of the European Parliament and of the Council ([17]) |
| | | Entities holding a distribution authorisation as referred to in Article 79 of Directive 2001/83/EC |
| Drinking water | | Suppliers and distributors of water intended for human consumption as defined in Article 2, point (1)(a), of Directive (EU) 2020/2184 of the European Parliament and of the Council ([18]), excluding distributors for which distribution of water for human consumption is a non-essential part of their general activity of distributing other commodities and goods |
| Waste water | | Undertakings collecting, disposing of or treating urban waste water, domestic waste water or industrial waste water as defined in Article 2, points (1), (2) and (3), of Council Directive 91/271/EEC ([19]), excluding undertakings for which collecting, disposing of or treating urban waste water, domestic waste water or industrial waste water is a non-essential part of their general activity |
| Digital infrastructure | | Providers of internet exchange points as defined in Article 6, point (18), of Directive (EU) 2022/ 2555 |
| | | DNS service providers as defined in Article 6, point (20), of Directive (EU) 2022/2555, excluding operators of root name servers |
| | | top-level-domain name registries as defined in Article 6, point (21), of Directive (EU) 2022/ 2555 |
| | | Providers of cloud computing services as defined in Article 6, point (30), of Directive (EU) 2022/ 2555 |
| | | Providers of data centre services as defined in Article 6, point (31), of Directive (EU) 2022/ 2555 |
| | | Providers of content delivery networks as defined in Article 6, point (32), of Directive (EU) 2022/2555 |

[14] Directive 2011/24/EU of the European Parliament and of the Council of 9 March 2011 on the application of patients’ rights in cross– border healthcare (OJ L 88, 4.4.2011, p. 45)
[15] Regulation (EU) 2022/2371 of the European Parliament and of the Council of 23 November 2022 on serious cross-border threats to health and repealing Decision No 1082/2013/EU (OJ L 314, 6.12.2022, p. 26)
[16] Directive 2001/83/EC of the European Parliament and of the Council of 6 November 2001 on the community code relating to medicinal products for human use (OJ L 311, 28.11.2001, p. 67)
[17] Regulation (EU) 2022/123 of the European Parliament and of the Council of 25 January 2022 on a reinforced role for the European Medicines Agency in crisis preparedness and management for medicinal products and medical devices (OJ L 20, 31.1.2022, p. 1)
[18] Directive (EU) 2020/2184 of the European Parliament and of the Council of 16 December 2020 on the quality of water intended for human consumption (OJ L 435, 23.12.2020, p. 1)
[19] Council Directive 91/271/EEC of 21 May 1991 concerning urban waste water treatment (OJ L 135, 30.5.1991, p. 40)

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| | | Trust service providers as defined in Article 3, point (19), of Regulation (EU) No 910/2014 of the European Parliament and of the Council ([20]) |
| | | Providers of public electronic communications networks as defined in Article 2, point (8), of Directive (EU) 2018/1972 of the European Parliament and of the Council ([21]) |
| | | Providers of electronic communications services as defined in Article 2, point (4), of Directive (EU) 2018/1972 insofar as their services are publicly available |
| Public administration | | Public administration entities of central governments as defined by Member States in accordance with national law |
| Space | | Operators of ground-based infrastructure, owned, managed and operated by Member States or by private parties, that support the provision of space-based services, excluding providers of public electronic communications networks as defined in Article 2, point (8), of Directive (EU) 2018/1972 |
| Production, processing and distribution of food | | Food businesses as defined in Article 3, point (2), of Regulation (EC) No 178/2002 of the European Parliament and of the Council ([22]) which are engaged exclusively in logistics and wholesale distribution and large scale industrial production and processing |

[20] Regulation (EU) No 910/2014 of the European Parliament and of the Council of 23 July 2014 on electronic identification and trust services for electronic transactions in the internal market and repealing Directive 1999/93/EC (OJ L 257, 28.8.2014, p. 73)
[21] Directive (EU) 2018/1972 of the European Parliament and of the Council of 11 December 2018 establishing the European Electronic Communication Code (OJ L 321, 17.12.2018, p. 36)
[22] Regulation (EC) No 178/2002 of the European Parliament and of the Council of 28 January 2002 laying down the general principles and requirements of food law, establishing the European Food Safety Authority and laying down procedures in matters of food safety (OJ L 31, 1.2.2002, p. 1)