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D2.2 Multi-hazard scenario building methods

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D2.2 Multi-hazard scenario building methods

Summary

Deliverable 2.2. of ICARIA outlines details relating to mathematical approaches and models that can be applied for quantifying the joint probabilities of compound multi-hazard events. The deliverable provides details as to the type of compound events that are to be modelled across the three case studies and through the review of previous works on multi-hazard modelling provides approaches for defining joint probabilities based on both correlation and physical interactions between modelled hazards.

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Document history

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28/02/2024	3.0	Barry Evans (UNEXE)	Final version for submission incorporating final suggestions

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3. List of Acronyms and Abbreviations

AMB	Àrea Metropolitana de Barcelona
BN	Bayesian Networks
FWI	Fire Weather Index
P	Probability
RP	Return Period
SAR	South Aegean Region
SLZ	Salzburg
SPEI	Standard Precipitation-Evapotranspiration Index
SSPs	Shared Socio-Economic Pathways
WP	Work Package

4. Executive summary

This document outlines work undertaken within the ICARIA project that seeks to develop an asset level modelling framework for assessing the potential implications of climate driven hazards that also considers the complexities associated with compound and cascading disasters. To demonstrate this framework the methods and tools developed in this project will be trialled across three selected regions in Europe (Barcelona, Salzburg, and South Aegean Regions).

With the effects of global warming leading to increased likelihood of compound hazard events there is the need for regions to develop means to facilitate multi-hazard analyses and assess how combinations of compound hazards can affect different sectors and find cost effective means to mitigate against such events. The previous deliverable 2.1. "Holistic modelling framework for multi-hazards and related uncertainty analysis" outlined the hazards being analysed within the respective case studies in the context of both single and compound hazard events, along with the physical modelling tools to be adopted and a summary of potential hazard interactions. This document expands on this work through defining methods that can be employed for developing multi-hazard scenarios, defining the likelihood of such scenarios occurring, and their potential consequences.

This deliverable (D2.2) consolidates information and results obtained throughout Task 2.2 "Extreme multi-hazards and modelling scenarios" within Work Package 2 (Modelling and Multi-Hazard assessment) of the ICARIA project.

The main objectives of this document can be summarised as follows:

- Outline the types of multi-hazard scenarios being modelled within ICARIA
- Provide overview of mathematical models for quantifying the joint probabilities of compound hazard events that considers:
    - Interdependency between hazards
    - Causality in hazard drivers
    - Uncertainties
- Outline approaches used for the modelling and quantification of compound hazard events
    - Joint Probability Analysis
    - Markov Chains
    - Monte Carlo Simulations
    - Bayesian Networks
    - Approaches for representation and visualisation of data from multi-hazard scenarios

1 Introduction

Between 1980 and 2020 there were around 1,117 reported natural disasters within the European Union (EU) and of those, over 93% were weather- and climate related (Gagliardi et al., 2022). Considering the implications of climate change it is expected that the frequency and severity of such events will increase. As such, effective steps and measures need to be implemented to mitigate against them (UNDRR, 2015). The potential devastating effects of these events will have greater implications to regions that are susceptible to multiple climate driven hazards. To combat this a "multi-hazard" assessment approach that considers variations in the location, extent, intensity, and frequency of these climate extremes will need to be considered (Forzieri et al., 2016).

As part of the Horizon Europe project **ICARIA**, funded by the European Commission, a comprehensive asset level framework for analysing the complexities and consequences that multi-hazard events may have to selected regions in Europe is being developed.

The framework being developed in ICARIA will assess the effects of six climate-driven hazards (Floods, Storm Surge, Heatwaves, Droughts, Forest Fires, and Storm winds) across three EU countries (Greece, Spain, and Austria). These hazards will be modelled individually, and as part of multi-hazard scenarios that consider compound coincident hazards (overlapping in space and time), and compound consecutive hazards (overlapping in space but occurring sequentially). These assessments will take place in the form of Trials and Mini-Trials within the respective case studies.

The "Trials", in this instance, will be carried out in the scope of "best case study" scenarios, where there is already good data availability and tools/experience in place to implement the models. The "Mini-Trials", in contrast, refer to adapting the modelling framework developed in the trials to derive assessments where the quality of available data may not be to the same standard as that used within the trials.

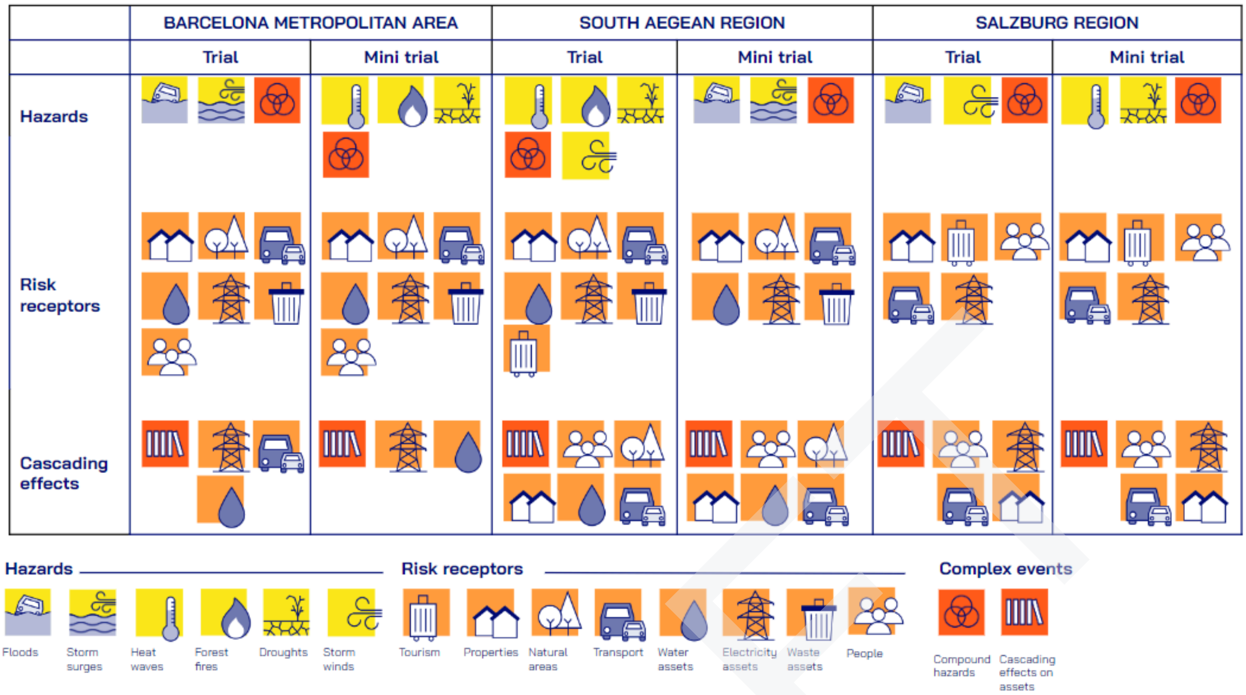

Figure 1. Summary of the Trial and Mini-Trials for each case study in ICARIA (ICARIA. 2023a)

2 Objectives of deliverable

Work Package 2 (WP2) within ICARIA focuses on the hazard component of the risk/impact assessment across the three case studies. Previous work from Task 2.1 (summarised in Deliverable 2.1 "Holistic modelling framework for multi-hazards and related uncertainty analysis"):

- introduced the three case study regions being assessed within ICARIA,
- the climate driven hazards that are to be modelled within these case studies,
- the tools being utilised to model these hazards,
- the physical interactions between different modelled hazards,
- and some historical data relating to multi-hazard events.

This deliverable builds upon this, considering the physical interactions/interdependencies between hazards to derive mathematical models/approaches for quantifying the probabilities of combined and compound multi-hazards under various scenarios, whilst also considering uncertainties caused by different environmental and humanitarian drivers. The models/approaches outlined within this document will be later adopted/developed by the case studies in later tasks based on their best fit for the data and hazards being modelled.

3 Background on multi-hazard scenarios

3.1 From single to multi-hazard perspective

The IPCC report 2022 outlined that as a consequence of global warming the number of compound hazards is increasing with particular emphasis on concurrent heatwaves and droughts, followed by dangerous fire weather, and floods (IPCC 2022). Typically, however, a common approach for modelling the consequences of climate extreme events is carried out in a "one at a time" manner (Russo et al., 2023).

To fully understand the risks a region is exposed to, a multi-hazard and multi-sectoral perspective is needed, allowing for a more comprehensive understanding of risks and highlighting more efficient ways to mitigate against them (Sendai Framework, 2015). Therefore, to more fully encapsulate the risks that climate driven events may experience within a region, for both current day and future scenarios, a framework for assessing multi-hazard events is required. This adoption of multi-hazard assessment approaches has been gaining traction over the years. Recent analysis of scientific publications within Google scholar of articles that discuss climate hazards that include the term "multi-hazard" in their document shows an increase over the last two decades with an accelerated increase in recent years (Figure 2).

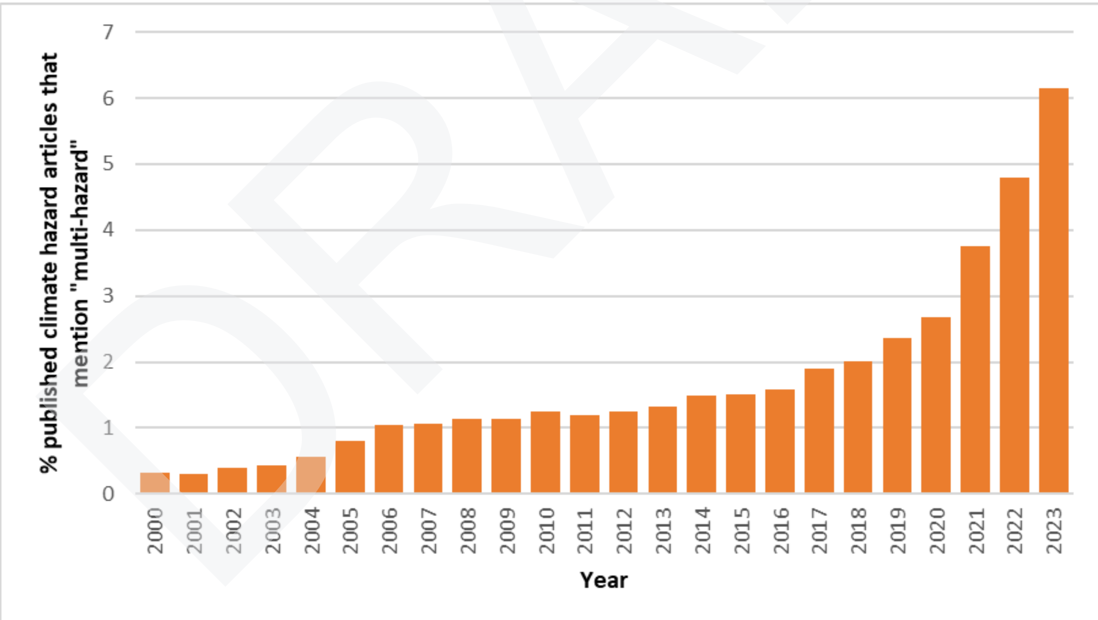

Figure 2. Percentage of published articles found through Google Scholar Search in Jan 2024, that mention the terms "multi-hazard" and "climate"

Transitioning from a single hazard modelling approach to a multi-hazard modelling approach is without its challenges since (1) the metric used to quantify the magnitudes of different hazard types may differ, and (2) there may be interdependencies between hazards where one hazard may influence the behaviour/characteristics, probability of occurrence of another hazard (Forzieri et al., 2016). In addition, a common approach used for interpreting the severity of independent hazard events is in terms of their probability of occurrence where more extreme events are deemed to be less likely to occur. However, when considering compound hazard events there may be causal relationships between them meaning the probability of Hazard Y occurring may be different if Hazard X is or has already occurred. Therefore, for hazards that share dependencies the probability of them both affecting a region may not simply be the product of their independent probabilities. For example, the probability of a wildfire occurring in a region that is experiencing drought can differ to that of a region that is not experiencing drought. In such scenarios where the probability of something changes based on new information, Bayes theorem can be applied (Bayes theorem is explained in more detail later in this document). Therefore, when carrying out multi-hazard analyses we need to clearly define types of compound events being considered, their respective interdependencies, and the causal relationships.

3.2 Classifications of multi-hazard scenarios

Within the ICARIA framework we are examining the implication of compound hazard events over time for both current and future climate change scenarios along with future Shared Socio-Economic Pathways (SSPs). For ease of definition, from the hazard modelling perspective we regard a multi-hazard event as being an event where the modelled hazards are affecting the same region (have overlapping spatial extents). With the spatial definition specified, from the temporal aspect we can consider multi-hazard events as:

4 Compound Coincident

Two or more hazards with overlapping spatial extents occurring either simultaneously or with overlapping timeframes. For instance, a low lying coastal region affected by compound flooding events due to storm surge coinciding with pluvial flooding.

5 Compound Consecutive

Two or more hazards (dependent or independent) with overlapping spatial extents but in place of overlapping time frames these events are occurring in sequence where the effects of previous hazard/s still influence the risk/impact of current hazard. For example, a sloped forested region previously impacted from extreme wind may have reduction in tree canopy cover resulting in increased surface runoff from rainfall events resulting in increased flooding.

From the modelling perspective, multiple hazards with overlapping spatial and temporal extents can be regarded as a multi-hazard event. Figure 3 from Claassen et al. (2023) depicts how different hazards can be grouped together into “events” based on the overlap of their spatial and temporal extents. In this example of four consecutive hazards we observe that two “events” can be derived where event 1 consists of hazards 1, 2, and 3, and event 2 consists of hazards 3 and 4. An additional consideration in this example is that the extent of hazards can change over time such as that highlighted in Figure 3 (b).

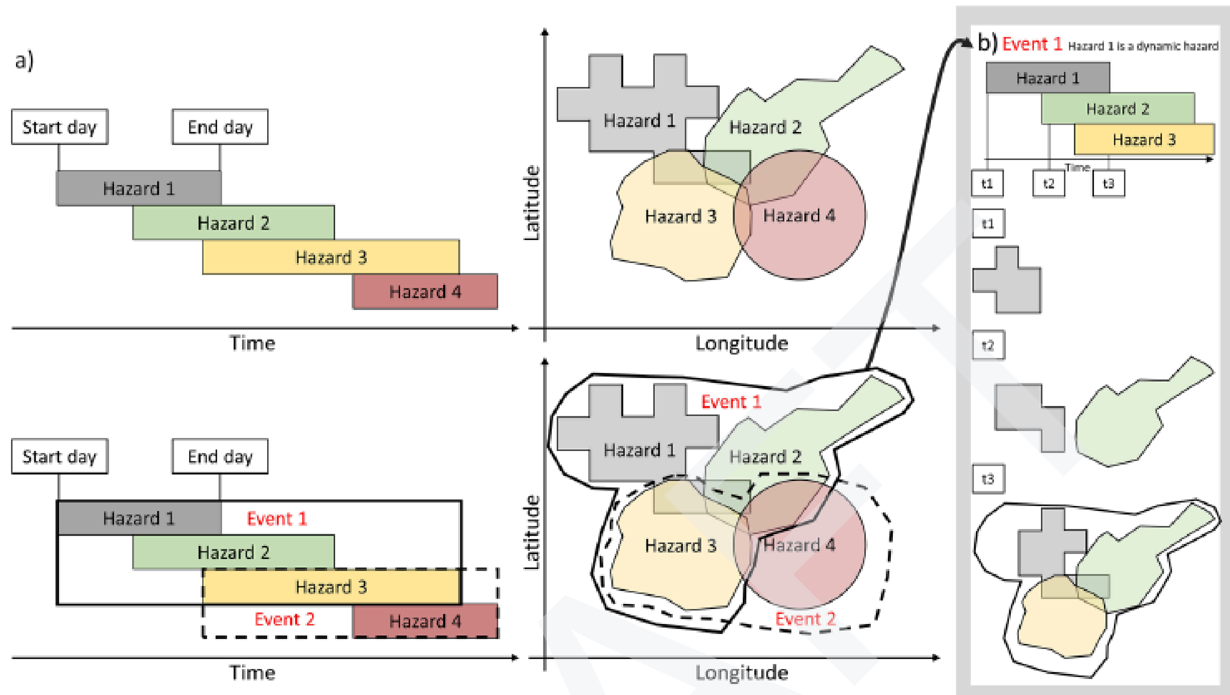

Figure 3. Example of how MYRIAD-HESA operates without a time-lag. This figure shows both hazard pairs and hazard groups. (a) Hazards are a hazard group if all hazards overlap with each other in space and time as a pair. Here, there are two hazard groups, which are referred to as Events. Event 1 is encompassed by the black solid line, while Event 2 is encompassed by the black dashed line. Event 1 consists of three hazard pairs between Hazard 1, 2, and 3. Event 2 consists of one hazard pair between Hazard 3 and 4. (b) A dynamic hazard has to overlap with the other hazards during at least one of the overlapping time-steps. Here, Hazard 1 is a dynamic hazard. Therefore, its event polygon can change over time. Hazard 2 and Hazard 3 are not dynamic hazards. Their polygons remain the same between their start time and end time (Claassen et al. 2023).

Based on these definitions of compound events, ICARIA is seeking to create a framework for modelling hazard chain pathways (Figure 4) that depicts a chain of events that begins within an initial triggering event and captures potential interactions with other hazards and triggering events over time along with consideration of future scenarios. To capture the implications of a chain of events like that depicted in Figure 4, we need to consider/define the interrelationships between the hazards. For this we consider the interrelationships for compound hazards outlined in Hielkema et al., (2021) where they can be defined as:

- **Independent**: Although hazards affecting the same region either simultaneously or in sequence, there is no triggering relationship or dependence between them. An example being an earthquake followed by a tropical storm.
- **Triggering or Cascading**: The effect of one hazard results in the triggering of subsequent hazard/s. For example, an earthquake followed by a tsunami.
- **Change conditions**: The environmental conditions within a region are changed as such where one hazard influences the likelihood of a secondary hazard occurring. For instance drought changing conditions of vegetation within landscape which in turn alters the likelihood of wildfire ignition
- **Association**: Where two or more hazards are the result of the same triggering event. Such as an extreme rainfall event occurring in a region with sloped terrain leading to flooding and landslides.

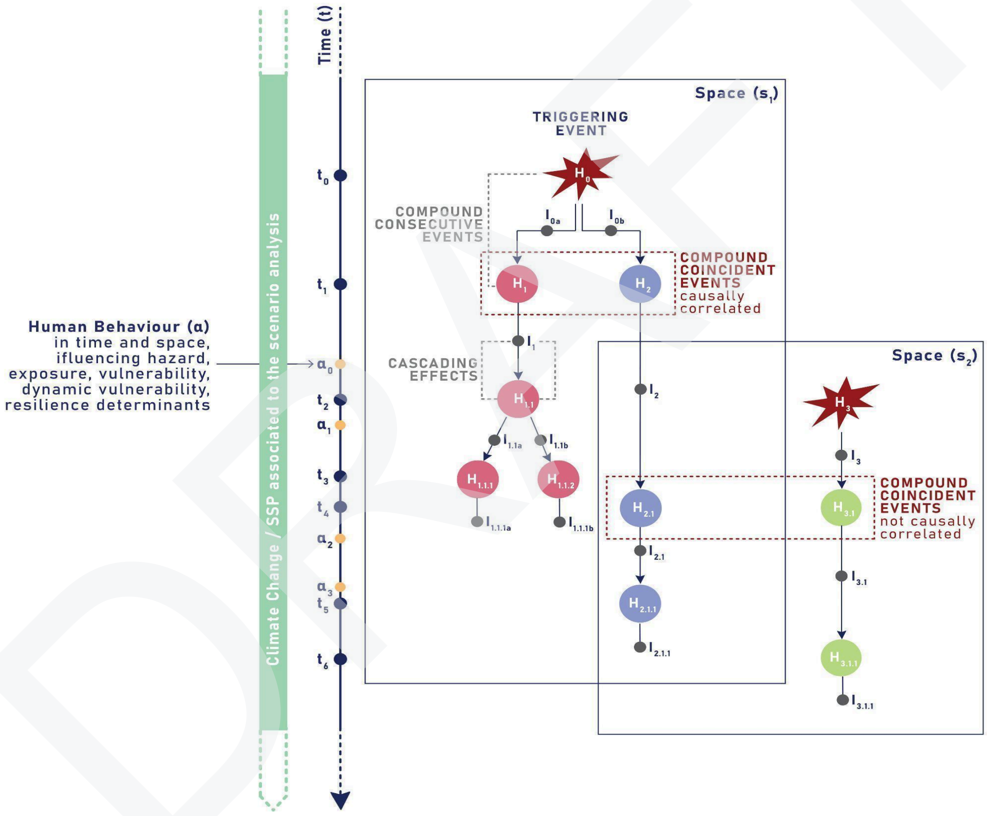

Figure 4. Timeline of events showing compound (coincident, causally or not causally correlated, and consecutive) events and cascading effects where "H" is Hazard, and "I" is Impact. The influence of key-variables (i.e., time, space and human behaviour) in the risk/impact/resilience assessment process has been considered (modified after Zuccaro et al., 2018) (ICARIA. 2023b).

5.1.1 Compound Coincident Hazards

For compound coincident hazards we are assuming that two or more hazards are affecting the same region within the same time frame and as such their compounding effects may result in a greater severity of hazard where each hazard can amplify the effect of the other. For instance the raising of water levels along a coast due to a storm surge can, in addition to coastal flooding, prevent the storm sewers from discharging to the sea, this reduction in drainage capacity from the catchment can result in further increases of flooding from pluvial side, this excess water can result in greater flood depths across the region including the low lying areas already affected by coastal flooding. To analyse the implications of such a scenario we need to define the causal relationship of these hazards occurring in the same region at the same time along with their physical interactions/interdependencies. Figure 5 provides a conceptual view for simulation of a compound coincident hazard. In this example the probability of occurrence is the joint probability of the event and is determined via the correlation of the hazard drivers and/or the physical interactions between the hazards. The resulting compound effects of the hazard are described by the physical interaction components that are then utilised as part of the impact assessment. When defining the interactions between hazards in this manner it is thus important to determine whether they are or are not causally correlated.

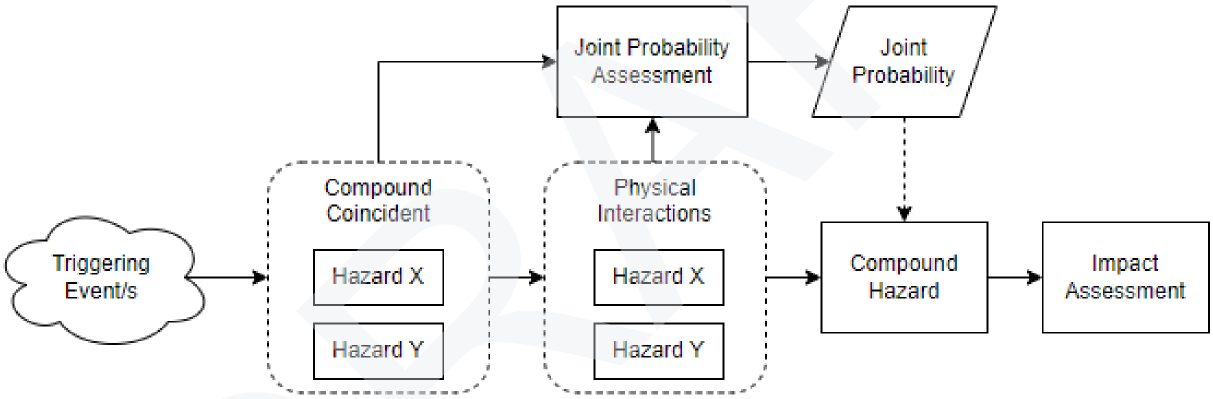

Figure 5. Conceptual view of defining likelihood of compound coincident events

Non causally correlated: If the two or more hazards are triggered by independent factors with no causal relationship between them then they are regarded as Compound Coincident (Independent) hazards. An example of such a combination could be that of an extreme rainfall event occurring during an earthquake. Whilst the combined effects of these hazards could lead to greater risks/impacts than that if they were to occur independently, there is no correlation relating to them occurring simultaneously. In such a scenario the probability of both hazards coinciding would therefore relate to their marginal probabilities as given by (Eq. 1).

$$P(X \cap Y) = P(X) \times P(Y) \qquad \textbf{Eq. 1}$$

Where:

- *P(X) = Probability of hazard X occurring*
- *P(Y) = Probability of hazard Y occurring*

As an example, the probability of a 1 in a 100-year earthquake event (p_eq = 0.01) coinciding with a 1 in 100-year rainfall event (p_rf = 0.01) would thus be a 1 in a 10,000-year event (p_comb = 0.0001).

Causally Correlated: In contrast to the above, some compound coincident hazards may be causally correlated, sharing common drivers. One example is where the effects of the first hazard influence the probability of the other hazard occurring. For instance, due to the potential changes in the physical landscape of regions experiencing a drought the probability of a forest fire occurring within those regions could increase. One approach for determining the probabilities of these types of events is that of Bayes theorem whereby the probability of a given hypothesis can be updated when presented with new information (Eq. 2).

$$Posterior\ Probability = \frac{Likelihood \times Prior\ Probability}{Evidence\ Probability}$$

$$P(X|Y) = \frac{P(Y|X) \times P(X)}{P(Y|X) \times P(X) + P(Y|\neg X) \times P(\neg X)} = \frac{P(Y|X) \times P(Y)}{P(X)}$$

Eq. 2

Where:

P(*X*|*Y*): Probability that *X* occurs given evidence or information *Y* (Posterior Probability)

P(*Y*|*X*): Probability of observing *Y* if the hypothesis *X* is true (Likelihood)

P(*X*): Probability of *A* being true (Prior probability)

P(*Y*|¬*X*): Probability of observing *Y* given *X* is false

P(¬*X*): Probability of the hypothesis *X* being false

P(*Y*): Probability of observing *Y*

For example, if we were to say the probability of a region being in drought *P(X)* is p = 0.15, and we derive from statistical analysis that probability of wildfire outbreak during a severe drought *P*(*Y*|*X*) is p = 0.7 and that probability of wildfire outbreak when no severe drought P(*Y*|¬*X*) (e.g. lightning strike, human activities) = 0.05. Substituting these values into equation 2 (Eq. 3), given a wildfire has occurred we can say that there was a(71% (p = 0.71) chance that it occurred during a drought.

$$P(X|Y) = \frac{0.7 \times 0.15}{(0.7 \times 0.15 + 0.05 \times (1 - 0.15))} = 0.71$$

Eq. 3

In addition to the interdependence between hazards there may also be correlations with the hazard drivers. For example, tropical and extratropical cyclones generate strong winds that can push water towards the coast resulting in storm surges; simultaneously heavy rainfall events are common within the vicinity of these cyclonic events due to the moisture being drawn up from the sea surface. These two drivers can result in a causally dependent compound flooding events from storm surge with pluvial flooding. For such events the probability of them occurring together requires other modelling techniques are required to define the joint probability. A commonly adopted statistical approach for defining joint probabilities for causally correlated events involves the use of mathematical functions known as Copulas. These functions and their application are outlined in more detail later in this document.

5.1.2 Compound Consecutive Hazards

Compound consecutive hazard scenarios refer to hazards with overlapping spatial extents occurring in sequence. In this example a triggering event could be climate driven such as the influence of climate change resulting in increases frequency and intensity of rainfall events leading to flooding, or hazard driven where the occurrence of a hazard could be a direct consequence of a previous hazard, for example an earthquake triggering a tsunami or the effects of a heatwave increasing the likelihood and severity of a forest fire. The conceptual representation of this type of compound event differs from that of compound coincident hazard in that the two hazards are now separated by time *(Δt)* (Figure 6). For the analysis of effects of compound consecutive hazards we need to determine how the effects of one hazard in the region will influence both the likelihood and magnitude of a following hazard.

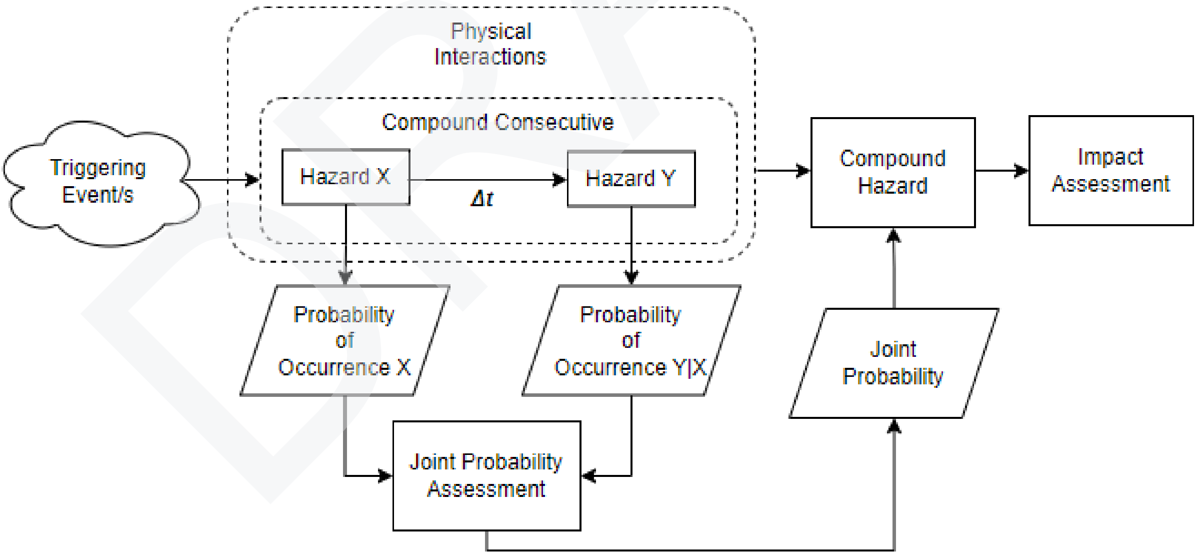

Figure 6. Conceptual view of defining likelihood of compound consecutive events

Within the scope of this document three kinds of compound consecutive hazards are considered

1. **Independent**: In this scenario hazard Y has occurred after hazard X but they are not causally related. An example of this could be similar to that outlined earlier relating to earthquakes and severe rainfall events. Unlike the previous example however, they are not occurring at the same time where there could be a period of days, months, or even years between the earthquake occurring and then the extreme rainfall event.
2. **Triggering**: For a triggering event the effect of the first initial hazard results in the causation of a secondary hazard. For example fluvial flooding along the base of slopes can cause increased erosion along the base affecting the stability of soil upslope potentially leading to landslides.
3. **Change conditions**: Here the effects of the first hazard within a region have changed conditions within that region that makes the likelihood of other hazards occurring increase. For instance, an extreme rainfall event within a region previously devastated by a forest fire, could result in significantly more severe flooding due to changes in landscape leading to increased surface runoff.

For defining the joint probability of compound consecutive events occurring, we therefore need to determine:

- Probability of Hazard X occurring,
- Probability of Hazard Y occurring,
- Probability of Hazard Y occurring over time given Hazard X has occurred

These requirements for defining the joint probability of compound consecutive hazards align with that of Bayes theorem outlined in Eq 2.

6 Summary overview of compound hazards to be modelled within ICARIA

6.1 Summary of physical interactions between modelled hazards in ICARIA

As outlined earlier in Figure 1, six hazard types have been selected to model within this project using respective hazard modelling tools that are detailed in Deliverable 2.1. (ICARIA 2023c) From these six hazards, seven multi-hazard scenarios have been selected to model across the three case study regions (Table 1).

Table 1. Multi-hazard scenarios to be modelled within ICARIA

Multi-Hazard Scenarios	Selected Case Studies
Storm Surge and Flooding (Pluvial)	AMB, SAR
Flooding (Fluvial) and Extreme Wind	SLZ
Drought and Forest Fire	AMB, SAR
Drought and Heatwave	AMB, SAR, SLZ
Heatwave and Forest Fire	AMB, SAR
Extreme Wind and Forest Fire	AMB, SAR
Drought, Heatwave, and Forest Fire	AMB, SAR

Various works have been conducted over the years outlining the physical interactions between hazards such as in De Pippo et al. (2008), Kappes et al. (2012), Tsoutos (2023) whereby the interactions between hazards are summarised within an interaction matrix. Referencing these works a hazard interaction matrix was defined for the modelled hazards within ICARIA that outline three of their possible independent relationships (Figure 7). This matrix provides a summary overview of both the physical interactions between the modelled hazards and insight into their causal relationships. The following sections provide a review of previous studies relating to each of multi-hazard scenarios in more detail to describe their potential interdependencies and causal relationships in more detail as a means of defining a framework to be adopted within this project.

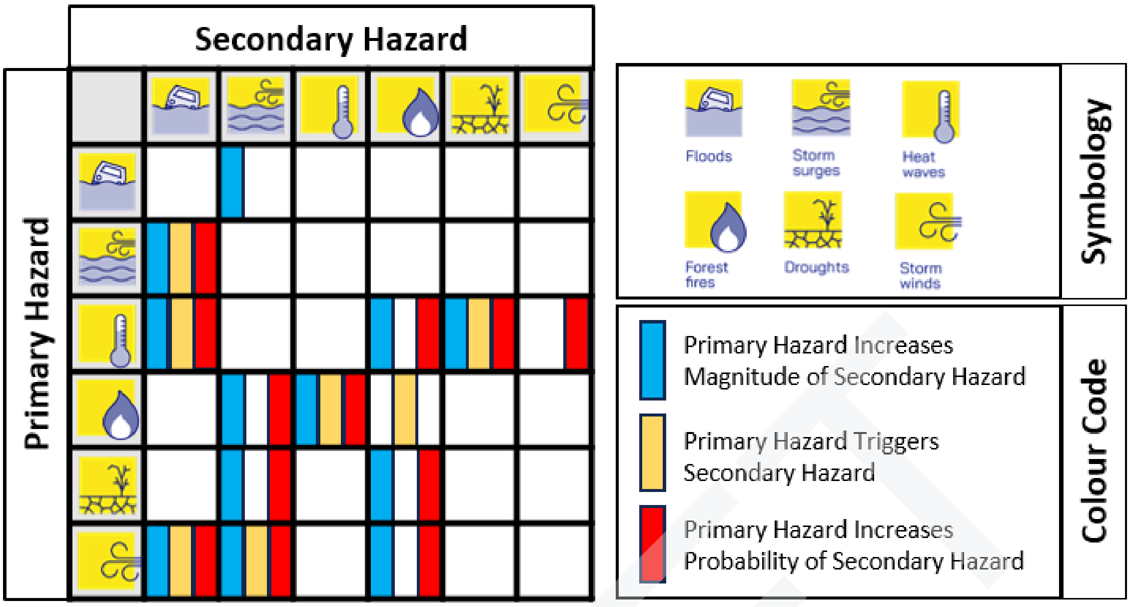

Figure 7. Hazard interrelationship matrix for modelled hazards within ICARIA (ICARIA 2023c)

6.2 Flooding (Pluvial) and Storm Surge

6.2.1 Physical hazards description and interactions

Sea level rise can increase the likelihood and severity of flooding due to backflow within the drainage system, and changes in boundary conditions at the land sea interface limiting the surface discharge capability.

From a single hazard modelling perspective IDF (Intensity, Duration, Frequency) curves can be utilised to define characteristics of synthetic rainfall events (Figure 8). Using these curves as reference, different extreme rainfall scenarios with defined probability of occurrences can be modelled to analyse the range of resulting flood hazards that can be generated. For instance, for a 1 in 10 year rainfall event, a flood model could be run with high intensity short duration hyetographs or low intensity but long duration hyetographs. Depending on the type of rainfall distribution being modelled and parameters relating to the catchment, for both these events that have the same return period, the flood extents could differ significantly.

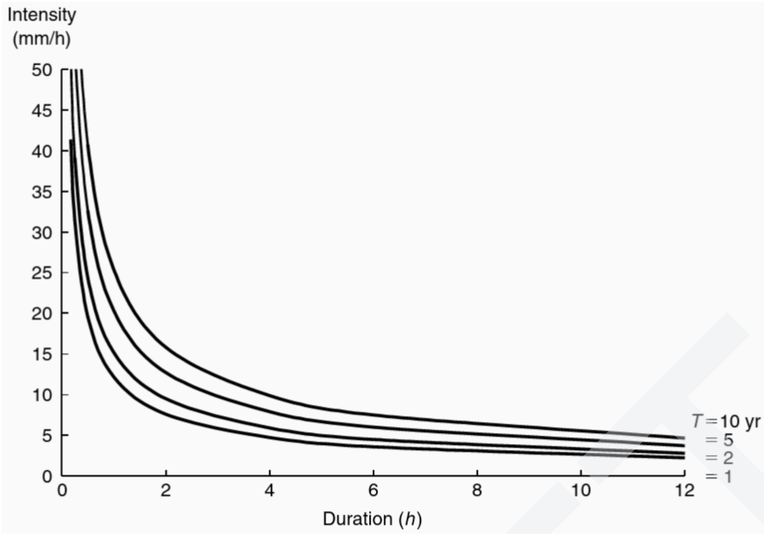

Figure 8. Typical intensity duration curves (Butler et al., 2018)

For low lying coastal regions high tides, storm surges, and wave conditions can lead to significant coastal flooding, whilst also leading to increased flood risks further inland within river catchment areas. An example of such a recent storm surge event is Storm Xaver that impacted Europe in 2013 leading to localised surges across the east of UK coastline and west European coastlines with a severity equivalent up to greater than a 1 in 1000 year return period in some regions (Figure 9).

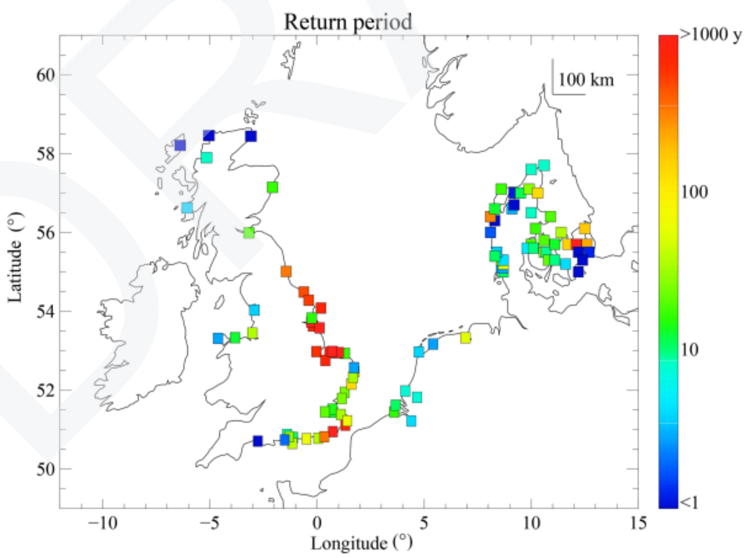

Figure 9. Map of reports relating to the severity of storm surges recorded over coastal areas in Europe during Storm Xaver (Kettle, 2020)

For compound flood events the influence of sea levels can affect the extent of flooding resulting from rainfall events by influencing regions capacity to discharge water at its boundaries, either directly from the surface or via the sewer systems. As such, storm surge events that coincide with extreme rainfall events can increase likelihood, trigger, and increase magnitude of flooding as reflected in Figure 7.

6.2.2 Considered climate variable dependencies

Previous works (Hawkes and Svensson, 2005; Xu et al., 2014; Zellou and Rahali, 2019; and Ming et al., 2022) examined the correlation between Storm Surges and Extreme rainfall events. In their work they identified correlations between different hazard drivers resulting in compound flood events. Figure 10 outlines an example of a bi-variate relationship depicting contours for tide level and rainfall (a), based on analysis of data from 1952 to 2009, and tri-variate surface depiction of compound rain, river flow, and surge events referencing to large historical data sets dating as far back as 1883 for flow data. In these examples, joint probability assessments were carried out, where historical data was analysed and through utilising Copula functions to define their interdependence relationships.

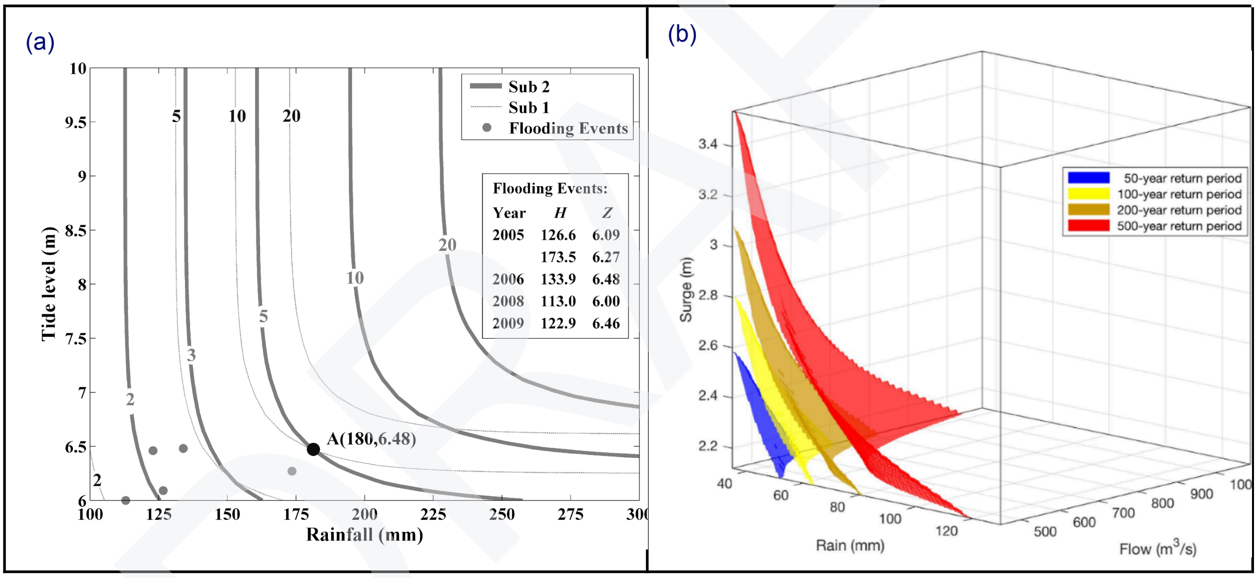

Figure 10. (a) Contours of the design joint RP for rainfall and tide level (Xu et al., 2014), and (b) hazard surfaces for rainfall, river flow, and surges (Ming et al., 2022)

6.3 Flooding and Extreme Wind

6.3.1 Physical hazards description and interactions

Extreme winds can influence the magnitude of fluvial flooding through altering the flowrate of the river and also limiting the river's ability to discharge downstream at the coastal boundaries if the storm winds are generating storm surges. An additional consideration relates to tree cover within mountainous regions, firstly the tree canopy serves as a protective buffer to incoming rainfall and secondly, the root structure from forested areas serve to help soil cohesion, particularly within sloped mountainous terrains (Ali & Osman, 2008) like those regions found in Austria. Damage to the tree cover due to extreme wind events can thus result in increased precipitation reaching the surface and at high intensities resulting in greater surface runoff and increased risks of soil erosion and landslides. Zhuang et al. 2023, highlighted that whilst the root systems of vegetation play a role in slope stabilisation, in sloped regions that are exposed to high winds such as typhoon winds experienced in Southeast China, the stresses on soil root interface caused by high winds on trees can result in increased infiltration of water along the root system soil boundary interface resulting in greater instability and leading to increased likelihood of landslides (Figure 11).

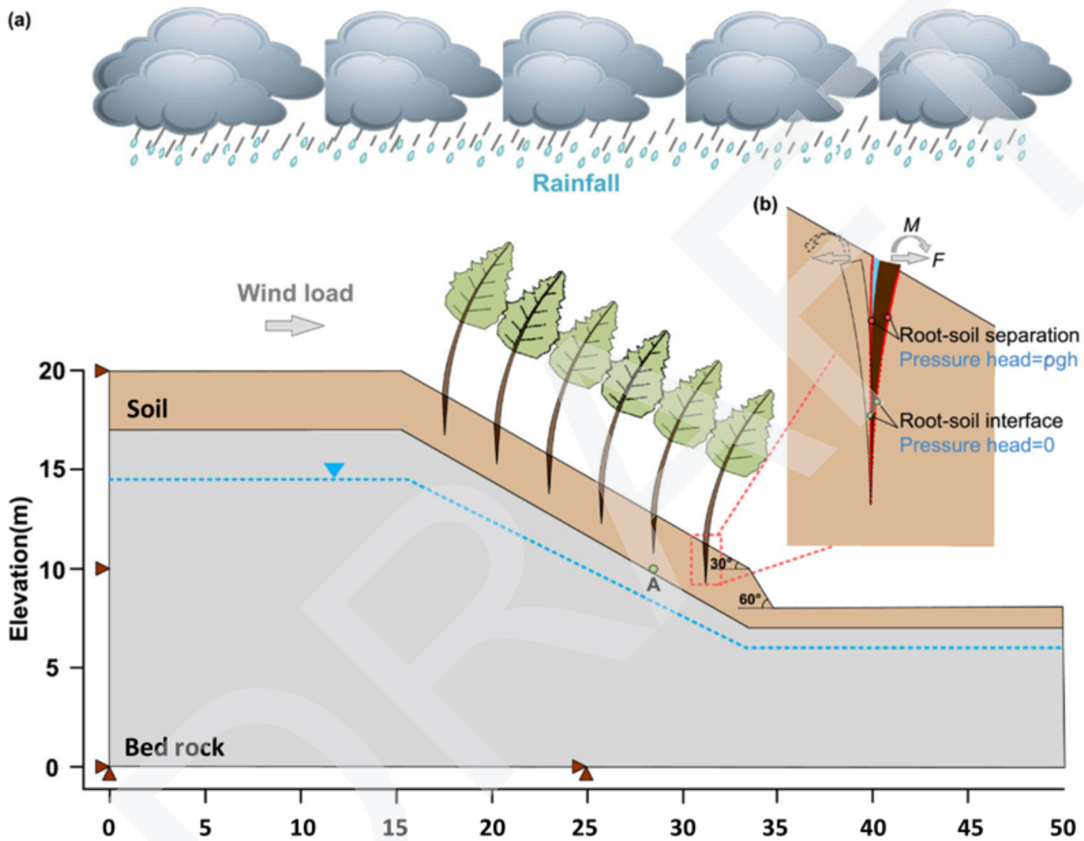

Figure 11. (a) Schematic diagram of Typhoon induced landslide (b) Principle of the preferential infiltration boundary (Zhuang et al. 2023)

An additional consequence of the damage that extreme winds can cause to tree canopies relates to the indirect consequences of debris blocking channels and inlets. This blocking of flow pathways can also result in an increase in both magnitude and likelihood of flooding events.

6.3.2 Considered climate variable dependencies

Whilst extreme wind cannot trigger increased precipitation events the combination of extreme wind and high rainfall events are interlinked via climate drivers, where within the EU the combination of extreme wind and severe rainfall events are driven either by extra tropical cyclones or summertime convective events (EU Commission et al. 2017). Previous work by (Bloomfield. et al., 2023), using Spearman's Rank correlation, have highlighted correlation between the occurrence of winter extremes for flood damage and wind damage across the UK and also the EU. In their analysis they showed there was strong correlation between extreme precipitation and extreme winds from daily to seasonal resolution where the correlation to extreme wind and river flows showed strong correlation between 40 - 60 days (with the lag assumed to be likely time required for soil saturation). As such the correlation of extreme wind and rainfall events needs to be considered when defining the joint probability of compounding wind and flood events.

6.4 Drought and heatwave

6.4.1 Physical hazards description and interactions

In the scope of drought modelling within ICARIA, drought is being assessed in the context of hydrological drought. For the combination of drought and heatwave, the compounding effects of these two hazards are planned to be assessed based on the additional pressures water resources are subjected to.

6.4.2 Considered climate variable dependencies

The IPCC report in 2022 highlighted that as a result of global warming there is high confidence that there will be an increase in the frequency of concurrent heatwaves and droughts for future scenarios (IPCC, 2022). For heatwaves in ICARIA, they are regarded as temperature-related episodes with a duration equal or greater than three consecutive days where the temperature is above the 95% percentile of the maximum daily records for the months of June to September during the period of 1985 - 2014. In the context of droughts they are considered based on the number of consecutive dry days (days where a threshold rainfall amount e.g. 1mm has not been exceeded). For ICARIA the Standard Precipitation-Evapotranspiration Index (SPEI) is being used to determine the onset, duration, and magnitudes of drought scenarios.

Previous work by Wang et al., (2023) analysed the relationship between compound droughts and heatwaves where they analysed the maximum temperature (Tmax) against monthly self calibrating Palmer drought severity index (sc-PDSI) dataset for both drylands and humid regions (Figure 12).

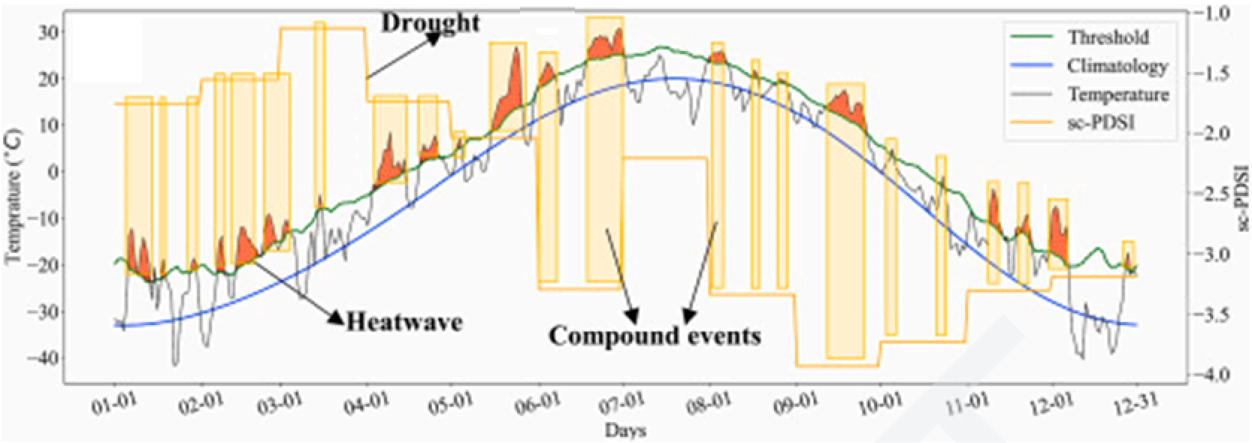

Figure 12. Schematic diagram of the mechanism of drought-heatwave compound events (Wang et al., 2023)

6.5 Drought and Forest Fire

6.5.1 Physical hazards description and interactions

The implications of drought on vegetation that serves as potential fuel source for forest fires leads to an increase in the probability of ignition and the rate of propagation of fires (Andrews et al., 2003; Scott & Burgan, 2005). In contrast, for periods of prolonged drought, the likelihood of fire ignition can reduce as the availability of fuels (vegetation) is reduced due die back from a lack of precipitation (NIDIS, 2024). As part of the forest fire modelling within ICARIA the creation of Fire Weather Index (FWI) scores for grid cells across the modelled regions will be generated. The derivation of these FWI scores comes from a number of parameters that relate to climate/weather drivers, fuel sources, and propagation (Figure 13). Within the compound modelling framework the effects of drought will influence the parameters used to define fuel sources thus affecting the resulting FWI scores.

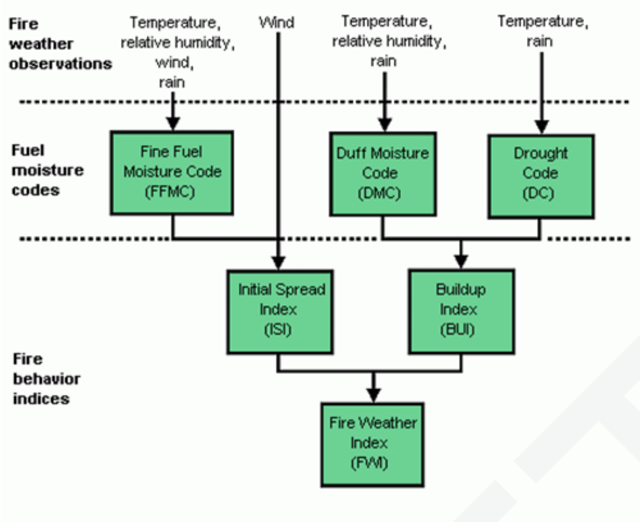

Figure 13. Components used within FWI derivation

6.5.2 Considered climate variable dependencies

During periods of drought, the probability of forest fire events occurring can increase (Littell et al., (2016), Chen, (2022)). Unlike previous examples, there is no directly modelled climate dependency analysed here, instead the consequences of the modelled drought scenario relate to the derived "fuel moisture codes" which are the drivers that potentially increase the likelihood of forest fires occurring and the subsequent extent/spreading, and duration of the fire. Therefore, for this model analysis of historical data, and computational modelling for a range of potential scenarios that correspond to different severities of drought and durations can be utilised to define the joint probability of forest fire occurring during or after periods of drought.

6.6 Heatwave and forest fire

6.6.1 Physical hazards description and interactions

Like that of droughts and forest fires the linkages between heatwaves and forest fires are well known contributing to the drying of land and subsequent increase in fuel sources for forest fires Rossiello & Szema (2019). As outlined in the previous "Drought and forest fire" section, temperature features within the fire weather parameters and directly influences components relating to the fuel moisture codes used to derive FWIs.

6.6.2 Considered climate variable dependencies

The combination of high temperatures, low humidity, and strong winds, generally termed as "Fire Weather" plays an important driver of wildfires, and due to the effects of climate change the length of fire weather seasons is increasing (Richardson et al., (2022), Calvin et al., (2023)). Like that of the drought and forest fire models the heatwave and drought models can assess the likelihood and severity of forest fire events based on different durations of heatwaves and temperature extremes.

6.7 Extreme Wind and forest fire

6.7.1 Physical hazards description and interactions

In addition to parameters relating to temperature and rainfall as utilised in the heatwave and drought models, wind also plays a significant factor in defining the FWI scores for a region (Figure 10). In addition to its consideration as part of the derivation of fuel moisture codes wind plays a direct role in the "fire spread" indices. Within the compound modelling the influence of extreme wind will be considered in the derivation of FWIs thus highlighting the potential compound effects of these hazards occurring simultaneously

6.7.2 Considered climate variable dependencies

In relation to correlation between wind and forest forest fires, regions that are susceptible to high winds may be at greater risk from forest fire events, in particular when considered with increased frequency of other fire weather drivers such as increased temperature, decreased rainfall, and prolonged periods of drought. An example of such conditions that has previously affected Austria was that of the Leppen, Bad Eisenkappel, Carinthia, forest fire in May 2020, that burnt an area of 23 hectares that was exacerbated by an ongoing drought in the region and persistent strong winds.

For the modelling climate dependencies for wind and forest fires, we must thus consider potential scenarios (both current and future) that implicitly take these additional aspects into consideration.

6.8 Heat Wave, drought, and forest fire

6.8.1 Physical hazards description and interactions

Previous sections have highlighted the relationships between these three hazards accordingly and based on these defined interactions the frameworks adopted will be integrated to explore this tri-variate combination of hazards. Previous analysis of these hazard interactions (Figure 14) at a pan-EU scale outlined in Sutanto et al., (2020) looked at both concurrent and consecutive hazards. Their findings found that drought were the main drivers for compound and cascading events.

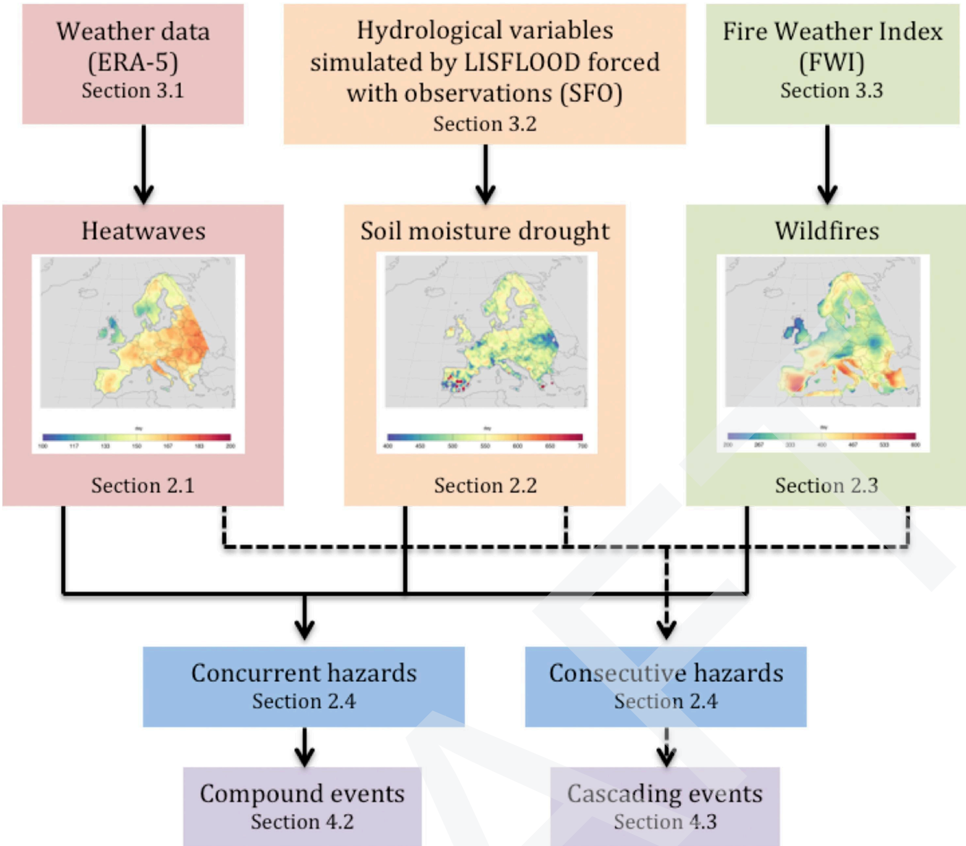

Figure 14. Flowchart describing the methodology and data adopted in study by Sutanto et al., (2020)

6.8.2 Considered climate variable dependencies

For the climate variable dependency approaches used for defining the joint probability drought-heatwave scenarios will first be defined to build an initial range of hazard drivers that will then be utilised to derive fuel moisture codes and respective FWIs. Through using this approach we can generate FWI map outputs similar to that shown in Figure 15 that spatially define regions susceptible to increase risks of forest fires when during compound drought and heatwave scenarios.

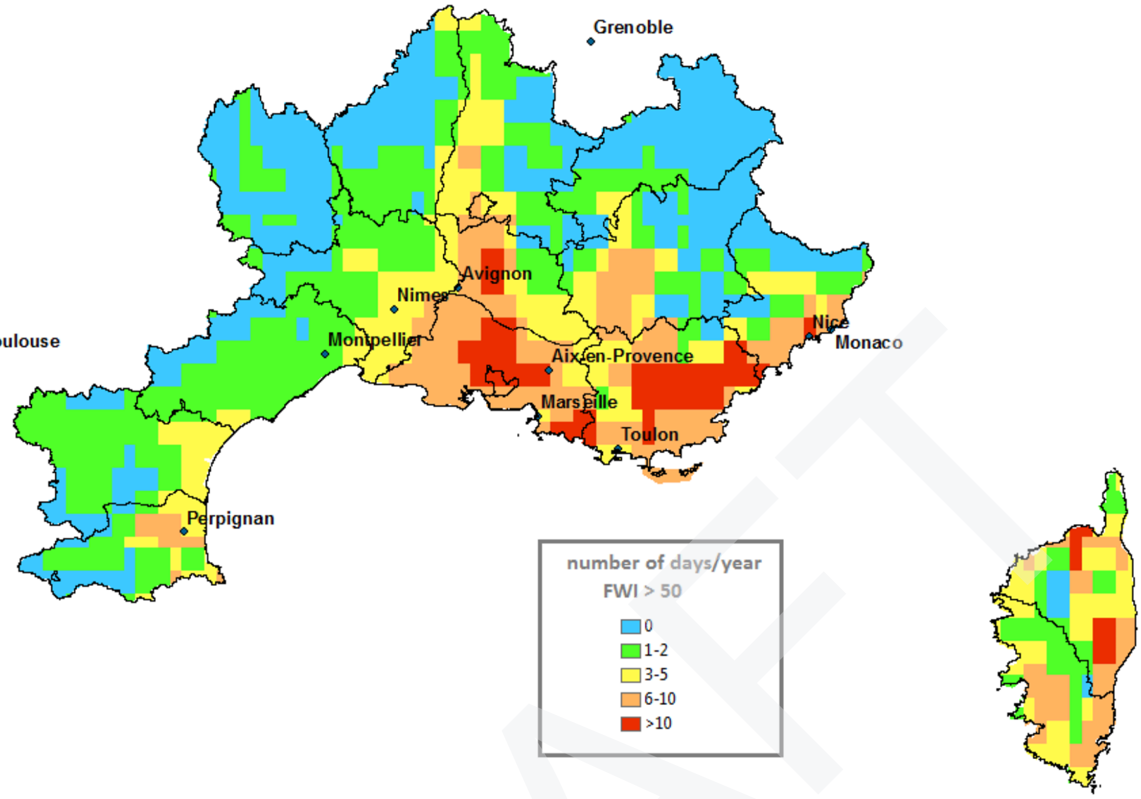

Figure 15. Example of Climatic model MPI/RCP8.5/number of days/year FWI > 50: period: 2036–2045 (Sfetsos et al., 2021).

7 Modelling dependencies between hazards being assessed within ICARIA

The holistic modelling framework being applied in ICARIA is based on the "elementary brick model" (Figure 16) whereby the compound hazard and impact assessments are broken down into fundamental components ("bricks") to analyse their properties and interactions. In this approach both time and space are considered in the generation of impact scenarios based on combinations of hazards as outlined previously in Figure 4. Further details relating specifically to this holistic modelling framework can be found in Deliverable 1.1: ICARIA holistic modelling framework.

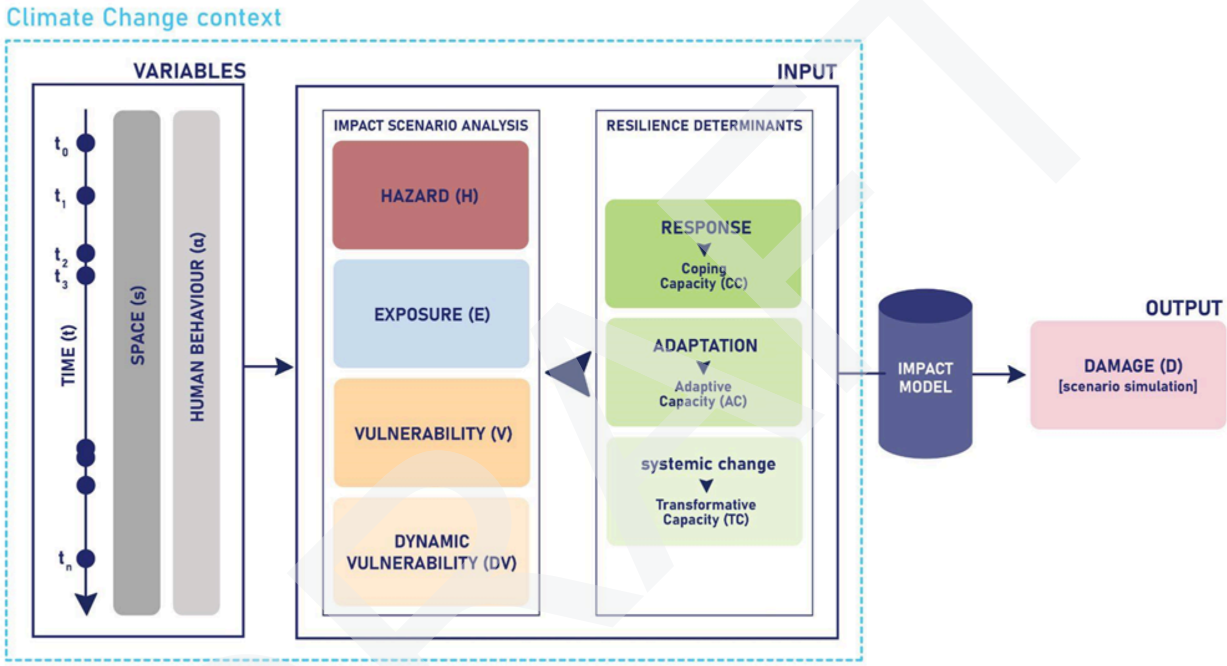

Figure 16. Holistic modelling framework for multi-hazard risk/impact/resilience assessment, covering combined events and their cascading effects. Main elementary bricks are represented (modified after Zuccaro *et al.*, 2018 and Russo *et al.*, 2023).

Within the impact scenario analysis section of the elementary brick model, we need to define the magnitude, duration, spatial extent, and likelihood of compound hazard events along with how the hazards influence the effects of each other. An approach outlined in Ming et al., (2022) represents the components of this section as three domains: **frequency analysis**, **flood simulation**, and **vulnerability and exposure analysis** derived from depth damage relationships defined in the multi-coloured manual to exposure (land-use classes) from the National Property Dataset (NPD) and Digimap that are then used for the multi-hazard risk assessment (Figure 17). In this approach the frequency analysis is used to define the joint probability distributions of modelled compound events;

selected events consisting of rainfall, river flow and storm surge values that define "joint extreme" scenarios are then physically modelled as part of the "flood simulation" domain.

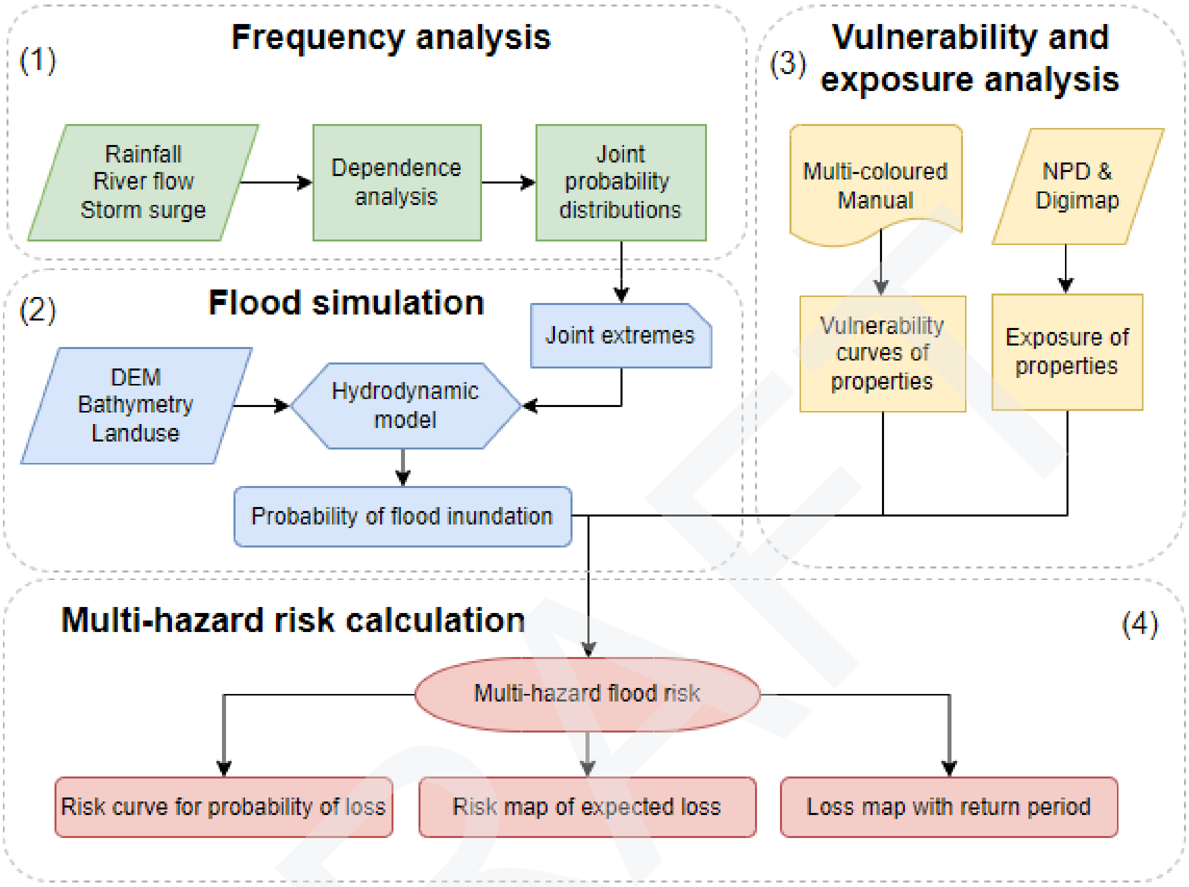

Figure 17. A multi-hazard risk assessment framework for compound flooding (modified after Ming et al., 2022)

Within the hazard assessment component of the ICARIA modelling framework a generalised approach is defined where for different combinations of compound hazards and scenarios (both coincident and consecutive , methods for defining dependency analysis and physical interaction between hazards will be used to define the hazard inputs that will be linked to the vulnerability and subsequent risk/impact assessment components, with and without resilience determinants. Figure 18 shows a generalised version of the approach to be adopted within ICARIA whereby the dependency and physical interactions between hazards are assessed whilst the results from compound hazard simulations are utilised as part of risk/impact assessment and also used in the derivation of joint probability based on dependency analysis.

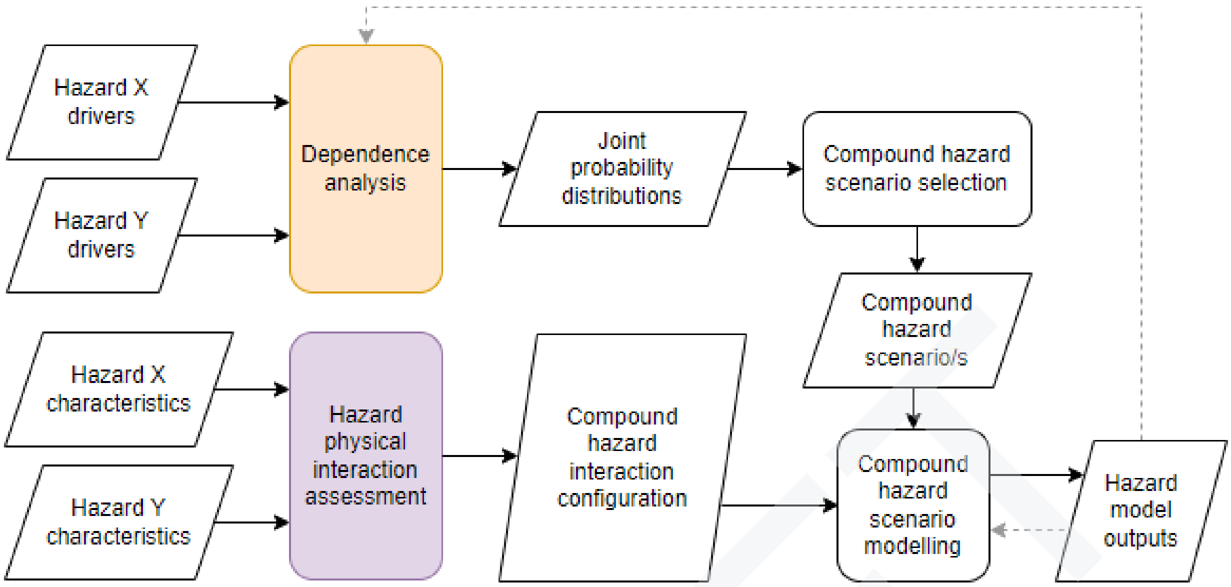

Figure 18. Conceptual framework for generating multi-hazard scenarios that considers frequency analysis, physical interactions, and feedback mechanisms for dependency analysis and consecutive hazard modelling

7.1 Defining joint probabilities of compound hazard events

7.1.1 Identification and selection of hazard drivers

When defining the joint probability of compound hazard events, we need to define the respective drivers of each hazard. These drivers could be climate drivers e.g. extra-tropical storm resulting in compound flooding of extreme rainfall with storm surge, or hazard drivers, extreme flood events leading to landslides.

With the identification of these drivers we can begin to assess the probability that these multiple hazards can lead to a compound event known as the joint probability.

7.1.2 Joint probability distributions and correlation

Where hazards share common drivers or interdependencies then their occurrence as a compound hazard will be defined via a joint probability. To define the joint probability of two or more hazards affecting the same region either at the same time or sequentially we need access to historical data relating to the drivers of the respective hazards. Once data for these hazards has been obtained the datasets can be assessed to look for correlation between them. There are a number of approaches for assessing correlation between compound hazards such as Spearman's rank (Bloomfield et al., 2023; Ming et al., 2022), that measures the strength and direction of association between ranked variables. An alternative could be the use of Pearson correlation coefficient that statistically quantifies the strength and direction of the linear relationship between variables where +1 means strong positive correlation, -1 means strong negative correlation and 0 means no correlation. If the analysis of the hazard datasets has shown the hazards to be correlated a number of approaches could be employed to assess their joint probability such as the use of copula models or Monte Carlo simulations.

Copulas are mathematical constructs originating from risk analysis within the financial sector that were later adopted for use within modelling risks associated with climate driven hazards. They are utilised to analyse the relationship/dependence between variables and have been applied in the context of analysing joint probabilities of compound events such as Pluvial, Fluvial, and Storm Surge flooding (Ming et al., 2022), Extreme Wind and Flood events in GB, and the EU (Bloomfield. et al., 2023) and heatwaves and droughts (Ballarin et al., 2021).

For Monte Carlo simulations, a large number of scenarios based on their individual probability distributions and correlations can be run. Analysis can then be carried out on frequency that both these hazards occur simultaneously (or sequentially) to estimate their joint probability.

7.2 Defining multi-hazard scenarios for current and future climate scenarios

7.2.1 Selection of compound hazard characteristics

When analysing the potential implications of compound hazard events, we first need to define the characteristics of the singular hazards being considered.

One of the challenges from a modelling perspective in the context of return periods (RPs) relates to the variations in model parameters that can correspond to that given RP. For example, in the context of flooding design rainfall events for different RPs can comprise different intensities for different durations. Therefore, for a given RP, there can be a range of intensity and durations that can be selected that can lead to different timings, magnitudes, and spatial distributions of hazards.

When examining the probability that a region may be affected by a given hazard or combination of hazards over time both the probability and the magnitude of that hazard occurring can depend on the previous state of the region. When modelling multi-hazard scenarios various aspects need to be considered including:

- Current State of System
- Time frames being considered
- Combination of Modelled Hazards
    - Return Periods/Probability of occurrence
    - Model parameters
    - Physical Interactions between hazards
- Spatial distributions of modelled hazards
    - i.e share same spatial extent Vs overlapping spatial extents
- Temporal relationship between hazards
    - Compound Coincident
    - Compound Consecutive

- Inclusion of adaptation and mitigation strategies
  - Where are these measures being applied
  - When are these measures being applied with respect to the modelling chain
  - How will these measures influence future states of model

7.3 Modelling interactions between hazards

In deliverable 2.1 details relating to the physical modelling of hazards and their interactions as part of compound coincident and compound consecutive events are outlined. Within this section we highlight methods for modelling a combination and/or sequence of events as shown in Figure 4 where three approaches modelling both the joint probability and magnitudes of these events are specified.

7.3.1 Markov chains

As part of the framework being developed within ICARIA the spatio-temporal relationships between hazards will be examined. From the modelling perspective such relationships can be captured in part via the use of Markov chains, where within a Markov chain the future state of a system is dependent upon the system's current state with this approach aligning with the modelling chain pathways outlined previously in Figure 3. From a multi-hazard modelling perspective, the influence of hazards to a system can be modelled in sequence where the state of the modelling space is updated as the model progresses through the chain. The probability of transitioning between states can be defined either via expert knowledge and/or on historical data, with the joint probability derived from the product of probabilities along the chain. Figure 19 outlines a simplified representation of a Markov chain depicting the probabilities of regions affected by extreme wind, and Flood. In this simplified example there are nine possible transition states (when we include states that feedback on themselves) as shown in Table 2. This example of a Markov chain highlights the prior state dependence whereby we observe a clear distinction between the probability of a region being in a flooded state (S_2) depending on whether its prior state is regarded as either being normal (S_0) or affected by wind (S_1). It is important to note that each of these states will also have a degree of uncertainty associated with them that will need to be considered in the modelling process when transitioning between states. The effects of this uncertainty can be modelled via consideration of variances within the initial starting state and the model parameters within the simulation that define state transitions.

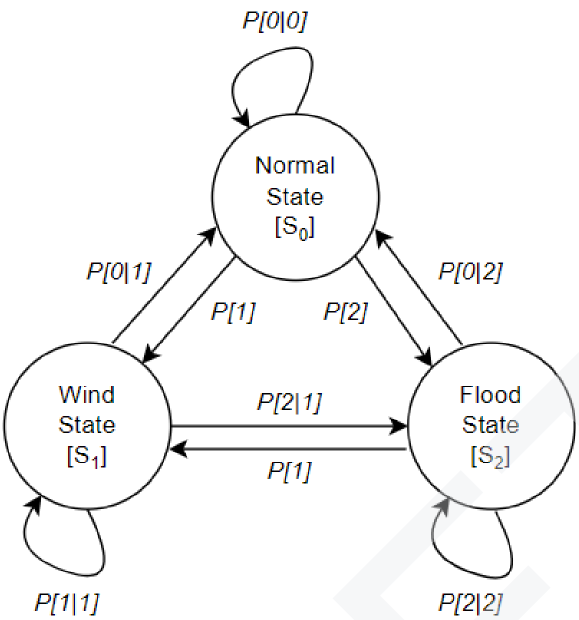

Figure 19. Example simplified Markov chain depicting two hazards

Table 2. Example transition states

	Normal	**Wind**	**Flood**
Normal	Normal → Normal	Normal → Wind	Normal → Flood
Wind	Wind → Normal	Wind → Wind	Wind → Flood
Flood	Flood → Normal	Flood → Wind	Flood → Flood

The data relating to state transitions can be written in the form of an adjacency matrix (Figure 20) where we explicitly define the probability of one state based on the condition of the prior state. In this example, the probability of transition from Normal to a Wind hazard affected region, the probability may be known based on the RP of the modelled event. For state transitions however like that of from Wind affected region to Flood affected region the probabilities would need to be determined via joint probability analysis methods. For determining the probability of flooding following an extreme wind event we can first model the potential change conditions to the regions as a result of simulating extreme wind scenarios. These simulations can give a range of potential outcomes for state S_1.

Note that in this configuration the transition from Flood hazard affected to Wind hazard affected is assumed to be the same as transition from Normal to Wind (P[1]) as flood hazard does not increase the likelihood of wind hazard occurring.

$$
\begin{array}{c|c|c|c|}
 & \text{Normal} & \text{Wind} & \text{Flood} \\
\hline
\text{Normal} & P[0|0] & P[1] & P[2] \\
\hline
\text{Wind} & P[0|1] & P[1|1] & P[2|1] \\
\hline
\text{Flood} & P[0|2] & P[1] & P[2|2] \\
\hline
\end{array} = A
$$

Figure 20. Adjacency matrix representation of example Markov chain

Based on this configuration the transition from a normal state to a flooded stated that has previously been affected by wind hazard (Figure 19) for a given combination of RPs for Wind and Flood is given by equation 4 where P[1] refers to the probability of a given Wind hazard event (*i*) and P[2|1] refers to the probability of a Flood hazard event (*j*) given that Wind hazard event (*i*) has occurred.

$$P_{0,1,2} = P[1] \,.\, P[2|1] \qquad \textbf{Eq 4}$$

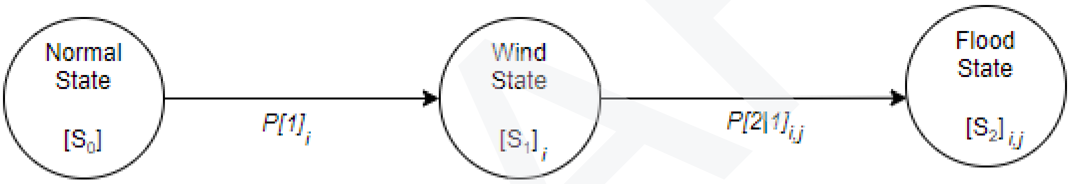

Figure 21. Transition from normal to affected by wind hazard then flood hazard states

This transition from $[S_0]$ to $[S_2]_{i,j}$ represents just one simplified example of transitioning between states. This Markov chain modelling approach however can be expanded to cover a range of hazard combinations and return periods over long time frames iterating transitions over multiple time steps whilst also allowing for the exploration/evaluation of adaptation measures to see how such measures reduce the probability of transitions between states and reduction of risks.

7.3.2 Monte Carlo Simulation

As previously highlighted, the number of variables and permutations associated with developing a multi-hazard perspective of risks within regions are particularly vast. Using a Monte Carlo approach, the variability between parameters within respective hazard models and their interactions can be modelled to estimate the likely outcome of compound consecutive hazards over modelled time frames.

Using a generalised example, consider that we want to evaluate the effect that Hazard Y has on a modelled region. Within a multi-hazard perspective, over time, there are various chains of events that can include Hazard Y. For a simple scenario (Figure 22) let's assume a small chain where Hazard Y occurs either directly from a Normal state or via a transition from a Normal state to a state affected by Hazard X that is then affected by Hazard Y. The initial state of the modelled region $(\boldsymbol{S_0})_i$ is defined with a range of setup parameters ***i*** and level of uncertainty (denoted by $\boldsymbol{U_0}$). The probability to transition from this $(\boldsymbol{S_0})_i$ state to a $(\boldsymbol{S_1})_{i,j}$ state for a given event is given by $P[1]_{i,j}$. where ***j*** relates to the modelled Hazard X and the resulting conditions of this state now being $(\boldsymbol{S_1})_{i,j}$. Transitioning from $(\boldsymbol{S_1})_{i,j}$ to $(\boldsymbol{S_2})_{i,j,k}$ for a new hazard event Y in this chain with a probability of occurrence of $P[2|1]_{i,j,k}$ where ***k*** relates to the parameters of the modelled hazard Y results in a final state for the region being $(\boldsymbol{S_2})_{i,j,k}$. Alternatively the region can reach state $(\boldsymbol{S_2})_{i,j,k}$ directly from $(\boldsymbol{S_0})_i$ for a modelled event with probability of $P[2]_{i,k}$. Therefore depending on the chain of events the resulting end condition of the region can vary. To capture these variations a Monte Carlo based approach can be employed where effects of different parameters ***i***, ***j***, ***k*** that relate to the state conditions and modelled hazard characteristics can be explored.

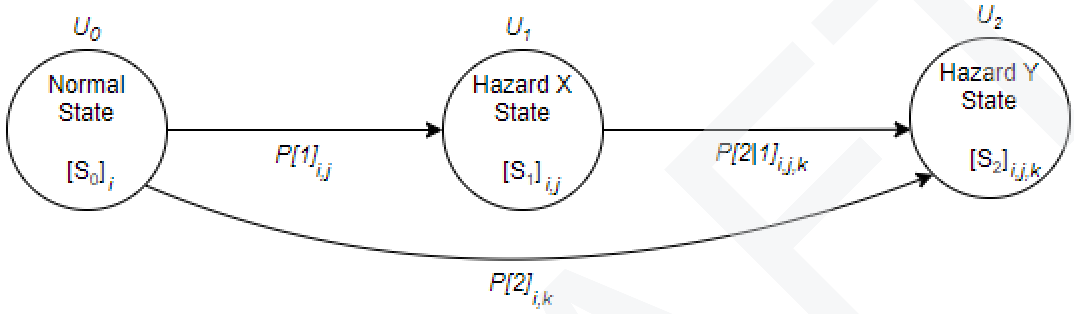

Figure 22. Tracing Markov chain of Hazard X followed by Hazard Y

An additional consideration not shown directly in the above example relates to the influence of time within the hazard chain modelling process. For example when modelling compound consecutive dependent events the condition of $\mathbf{S_1}$ may over time revert back to $\mathbf{S_0}$ condition thus when modelling the effects of consecutive hazards the temporal aspect needs to be considered.

With the range of potential parameters that can be considered when defining multi-hazard scenarios we need to establish/prioritise which parameters and variables will be assessed. To do this for the modelled hazards we need to:

- **Identify key variables**: Select variables or parameters within the respective hazard models that are of interest and are likely to influence the outcome of simulation
- **Understand sensitivity**: Carryout sensitivity analysis of parameters of potential interest to see how variations in these parameters may influence results
- **Consider uncertainties**: e.g. parameters with higher levels of uncertainty may give greater range of influence on the model
- **Define a balance between complexity and feasibility**: Due to model limitations, data, and resources it may not be feasible to model a vast number of scenarios. Therefore consideration is needed as to level of complexity required in order to provide meaningful results

Based on these considerations the modelling space for Monte Carlo simulations can be defined.

7.3.3 Bayesian Networks

Within the scope of multi-hazard scenarios Bayesian networks can be applied to model the complex interdependencies between different hazards and the potential risks/impacts associated with these hazards. A review of the potential of BNs by (Sperotto et al., (2017) in the context if climate change impacts showed that BNs have potential applications in:

- **System definition**: Combine information from different sources allowing for expert knowledge to be utilised with quantitative data
- **Exploring interactions**: A means of understating the complex interactions between modelled systems.
- **Quantifying interactions**: Enables complex interactions to be quantified in a probabilistic manner and allows for a more overview perspective of interactions to facilitate understanding of the system being analysed.
- **Uncertainty estimation**: Through the incorporation of both data and expert knowledge BNs allow for uncertainty to be expressed in more communicative way
- **Risk prioritisation**
- **Risk management**
- **Monitor and review**

Previous works have demonstrated the use of Bayesian Networks (BNs) for multi-sectorial (Harris et al., 2022) and multi-hazard (Vatteri et al., 2022) perspectives. In Harris et al., (2022), they applied a BN for the assessment of flood risks to different sectors that encompasses variations that considers flood depth (FDE), flood duration (FDU), and Flood Velocity (FDU) as part of the hazard drivers along with variations present in both exposure (Area of reported damage (ARE), and population density (POP)) and vulnerability parameters including land use cover (LU), population under 5 (POP_5), population over 65 (POP_65), number of houses with 1 story (FLO_1), number of houses with more than 1 story (FLO_N), number of houses with good conservation status (Con_G), number of houses with bad conservation status (CON_B), minimum residential market value (MV_MIN), maximum residential market value (MV_MAX), and Digital Elevation Model (DEM) (Figure 23).

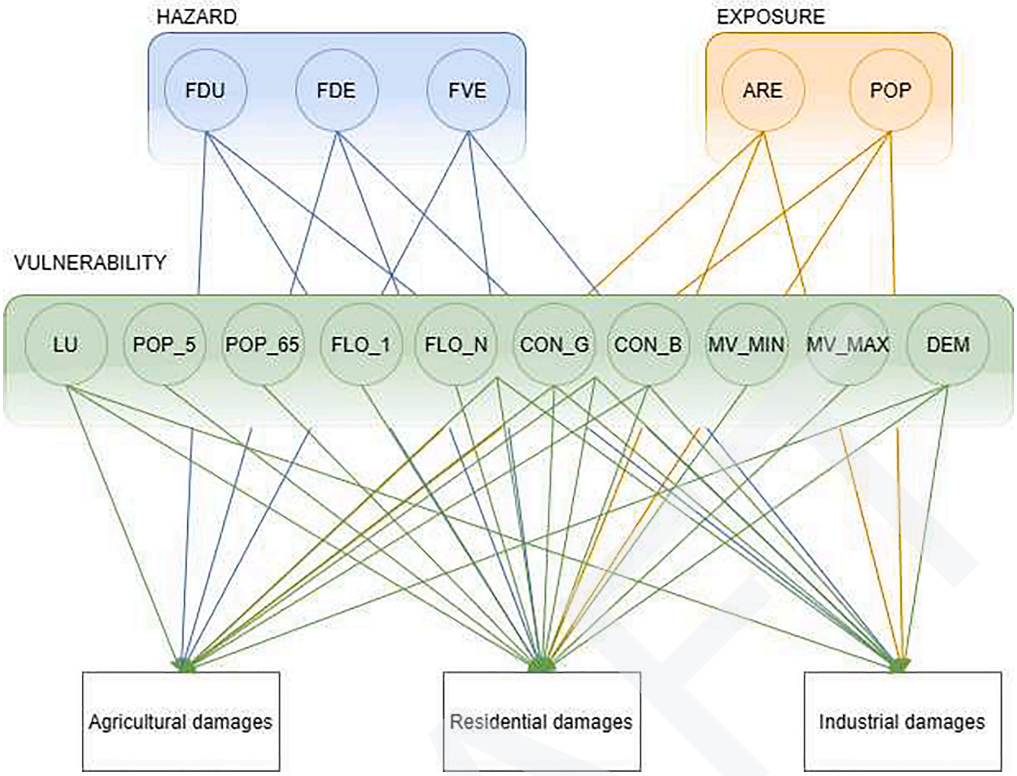

Figure 23. Conceptual framework of risk based BN for flood risk assessment (Harris et al., 2022)

From the hazard modelling perspective there are a variety of design/configurations of BNs that could be utilised to define the level of threat posed by compound (coincident and consecutive) hazards. For example Figure 24 depicts a conceptual BN network model where combinations of different RPs for compound flooding events. As highlighted previously in section 4.2, for compound flood events with defined return periods there can be a range of different rainfall values and tide levels that correspond to that return period. Through modelling a range of combinations of rainfall and tide level for each RP we can create a probability distribution that corresponds to the hazard threat level that could be calculated from flood depths and flow velocity distributions that are derived from flood model simulations. This BN with hazard threat levels defined can then be expanded upon to capture variations associated with vulnerability, exposure, and mitigation measures.

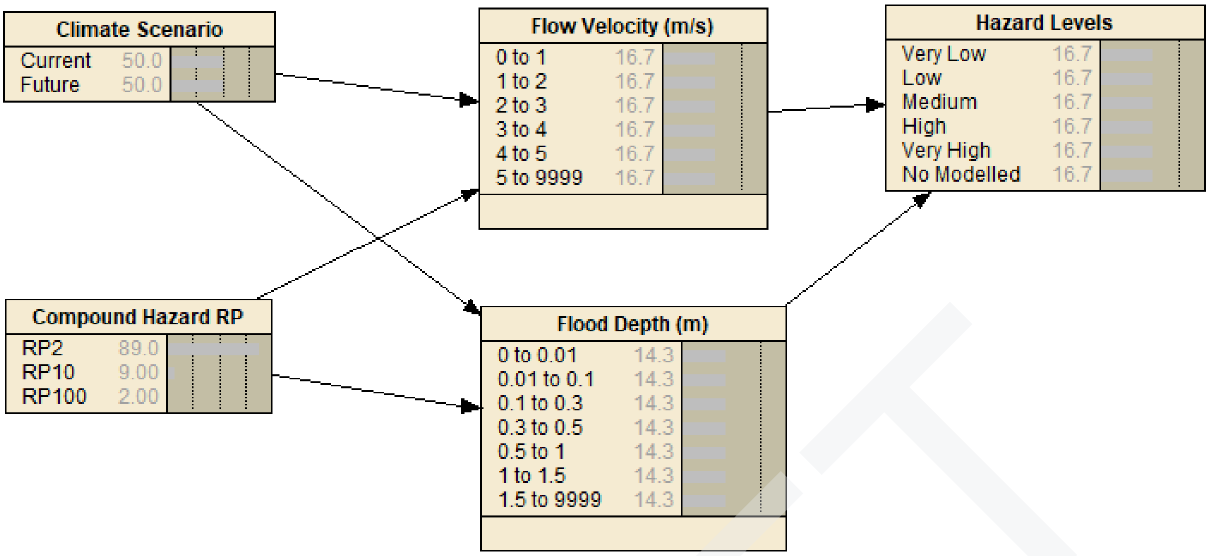

Figure 24. Conceptual Bayes Network for compound flooding for defined RPs

7.4 Quantifying and visualising hazards for compound events

From the quantification and visualisation perspective, the depiction of compound hazards events presents a challenge due to the different characteristics relating to each hazard. One approach is to classify hazards according to their relative intensity scales. Table 3 gives examples of three hazard types classified into three intensity classes of "low", "medium", and "high".

Table 3. Sample of ARMONIA hazard intensity classification matrix for a regional scale (Kappes et al., 2022)

Natural Hazard	Intensity Scales			
	Low	Medium	High	Parameters
Flood	<0.25	0.2-1.25	>1.25	Flood depth (m)
Forest Fire	<1.2	1.2-2.5	>2.5-3.5	Approximate flame length (m)
Seismic	<10	1–30	>30	Peak ground horizontal acceleration (%g)

Through analysis of historical events and/or modelling a range of hazard scenarios these classes can be expressed in the form of a magnitude-frequency relationship (Figure 25) (Kunz and Hurni., 2008) .

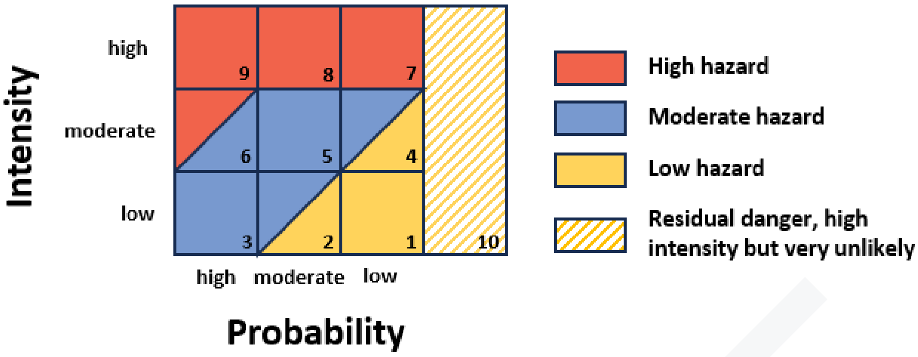

Figure 25. Magnitude-Frequency depiction of hazards (Kunz and Hurni., 2008)

The magnitude-frequency classification approach can be applied to multi-hazard assessment for the depiction of multi-hazard assessment that considers the uncertainties present within the multi-hazard modelling along with the range of potential multi-hazard scenarios. For example if we consider a compound consecutive events over a given time period we can analyse the variations in the magnitude of hazards that infrastructures are exposed to that considers uncertainties within the modelling framework and variations in time interval between respective hazards.

Figure 26 depicts an application of the proposed methodology for quantifying the magnitude-frequency distribution of storm winds followed by flooding over a designated time span ***T***. For simplicity, the scenarios presented in this example do not depict variations in spatial extent/overlaps, although such spatial considerations can be integrated into scenario definitions.

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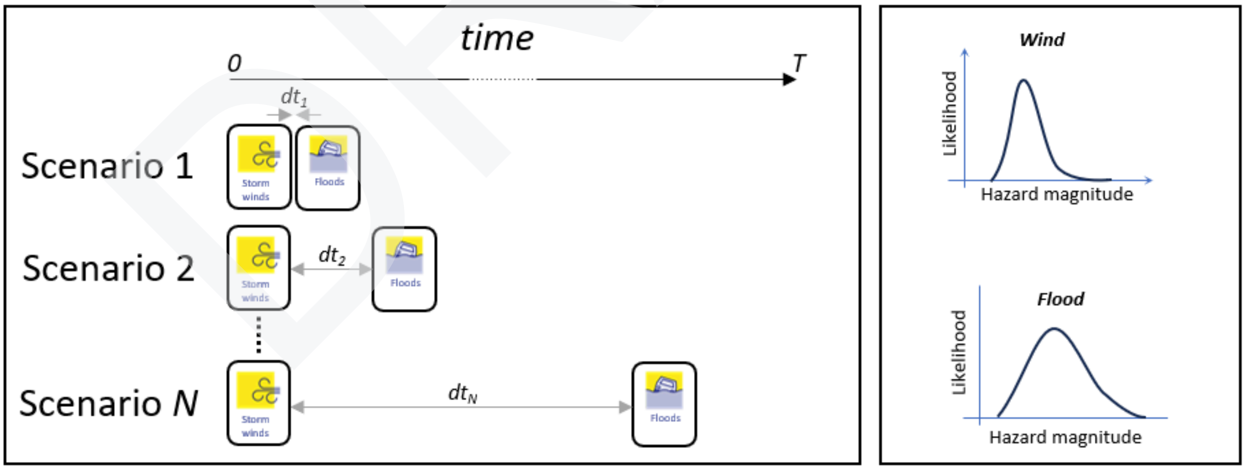

Figure 26. Example generation of probability distribution curves for compound consecutive hazard scenarios

In this scenario-based modelling approach each grid cell within a modelled domain would have an associated probability distribution function (PDF) generated by the wind hazard modelling that considers the model configuration and uncertainties present in the model. To translate this into a magnitude-hazard score the PDF is divided up according to the intensity scale (Figure 27) and cumulative probabilities are derived considering the upper and lower boundaries as defined in Table 4. For visualising CDF scores spatially the corresponding CDF score for the highest hazard class could be utilised that would convey to the stakeholders the distribution and likelihood of most severe hazards across the modelled region.

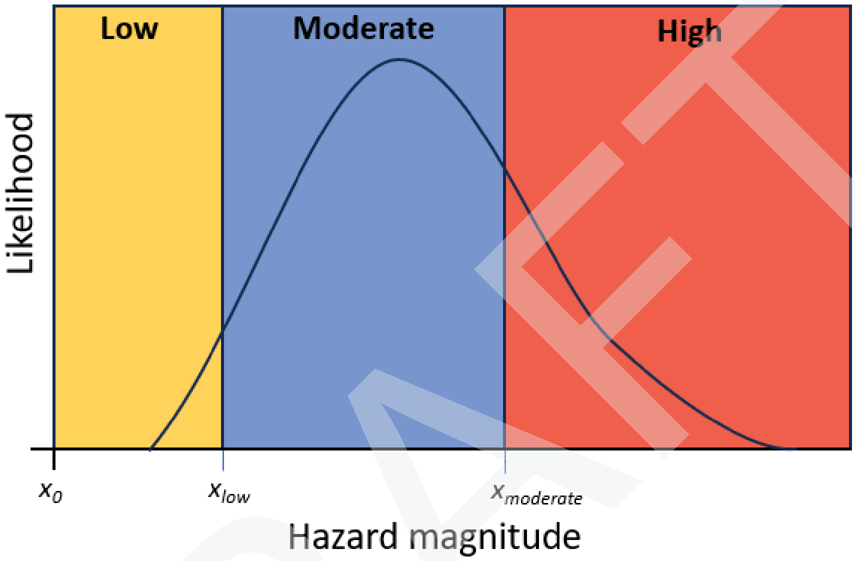

Figure 27. Classifying magnitude-frequency relationships for modelled hazards into three classes

Table 4. Example equations for deriving CDF values for hazard classes

Hazard CDF Class	Equation
Low Hazard CDF	$P(x_o \leq X \leq x_{low}) = \int_{x_0}^{x_{low}} g(x)dx$
Moderate Hazard CDF	$P(x_{low} \leq X \leq x_{moderate}) = \int_{x_{low}}^{x_{moderate}} g(x)dx$
High Hazard CDF	$P(X > x_{moderate}) = \int_{x_{moderate}}^{x_{\infty}} g(x)dx$

Continuing with the multi-hazard modelling framework the outputs of the wind hazard model would define the relevant input parameters for the flood model. In this context the physical characteristics of the modelled region between hazards, these can change over time, either through natural recovery of the region and/or other man-made interventions during this period. Based on a range of modelled scenarios a probability distribution function (PDF) curves for flood hazard will also be created with the derivation of magnitude-frequency scores for this hazard derived in the same manner as wind though with different threshold values for low, moderate, and high hazards.

This PDF to CDF and magnitude-frequency approach can also be applied for compound coincident events, where variations in spatial extents, the range input parameters associated with modelled return periods, and modelled uncertainties can be considered in scenario generation.

In the context of compound coincident events, uncertainties arise from the variations in model configurations and hazard interactions, as well as the wide range of parameters involved in selected scenarios. As highlighted earlier in Figure 9, for a given return period, a compound coincident flood event may encompass a diverse range of storm surge wave heights and rainfall intensities combinations. As such the magnitude and extent of flooding within the modelled region may vary. By using a PDF representation of the hazard metrics for a range of these combinations a PDF representation of compound coincident hazard can be depicted.

For the latter impact assessment side the generated PDF curves (g_x (x)) can be utilised with vulnerability data such as fragility curves (F_r (x)) to determine its limit state probability (P_f) that represents its probability of failure with respect to modelled hazard (Lee and Rosowsky., (2006)) (Figure 28). From a monetary loss perspective the fragility curve (F_r (x)) can be replaced with hazard Vs damage functions such as for in the context of flooding depth-damage curves.

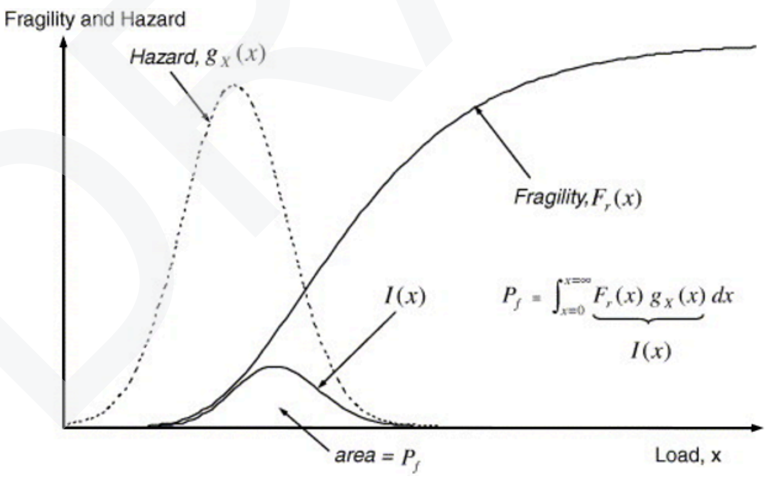

Figure 28. Determination of limit state probability (single hazard) (Lee and Rosowsky., 2006)

8 Conclusions

Over the last couple of decades there has been significant increase in research related to investigating multi-hazard events, driven, in part by the increased frequency of such events occurring and their impacts across different sector (Tripathy et al., 2023), and improvements in modelling and mathematical approaches for quantifying the impacts and likelihood of these events occurring.

Within the context of understanding the risks that climate hazards pose to a region, it is thus important from a multi-hazard perspective, to have a more comprehensive understanding of risks and facilitate policy makers in defining effective adaptation measures.

As part of Work Package 2: Modelling and multi-hazard assessment in ICARIA this document outlines a general overview of the different hazards being assessed across the three case studies and approaches that can be utilised for assessing the likelihood of compound coincident and compound consecutive hazards occurring.

As a generalise summary framework for understanding mechanisms for defining the level of threats posed from multi-hazard events the document suggests the following:

1. **Hazards that the region is susceptible to**: Identify which hazards pose significant risks to the region
2. **Hazard classification metrics**: Define the metrics used for determining the magnitude and probability of occurrence for modelled hazards
3. **Causality of hazard drivers**: Through a combination of expert knowledge and the analysis of historical hazard driver data establish whether the drivers of modelled hazard events are correlated
4. **Physical interactions between hazards**: Define if and how hazards interact with each other including:
    a. how one hazard influences the magnitude of the other hazard
    b. if one hazard triggers or increases the likelihood of another hazard occurring
5. **Define compound hazard scenarios**: Based on the prior points, define the joint probabilities for compound events and select the compound scenarios of interest for modelling within the region.
6. **Methods for quantification of compound hazards**: With physical interactions on probabilities defined, establish a method for quantification of compound hazard scores so that the model results can be utilised for risk and impact assessments.

Using the findings within this document the next steps will be to define the models, and compound scenarios for each of the modelled compound hazard configurations across the case studies as part of tasks 2.3 Coupled hazard models: methodology and tools, and task 2.4 WP2 lab: testing of methods and tools.

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Annex A: Data Management Statement

Table A1.1. Data used in preparation of ICARIA Deliverable 2.2

Dataset name	Format	Size	Owner and re-use conditions	Potential Utility within and outside ICARIA	Unique ID
n/a					

Table A1.2. Data produced in preparation of ICARIA Deliverable 2.2

Dataset name	Format	Size	Owner and re-use conditions	Potential Utility within and outside ICARIA	Unique ID
n/a					

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