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Theme 6: Environment (Including Climate Change)

Novel indicators for identifying critical *INFRA*structure at *RISK* from Natural Hazards

Deliverable D3.4 – Single Risk Analysis

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Abbreviations

BN	Bayesian Network
CDF	Cumulative Distribution Function
CI	Critical Infrastructure
EDP	Engineering Demand Parameter
GEV	Generalized Extreme Value distribution
GMPE	Ground-Motion Prediction Equation
IM	Intensity Measure
PDF	Probability Distribution Function
PGA	Peak Ground Acceleration
PGV	Peak Ground Velocity
Sa (Sd)	Spectral Acceleration (Displacement)

Executive Summary

This report proposes a mapping of the successive variables and models that are involved in single risk assessment, for each of the hazard types considered (i.e. earthquakes, landslides, fluvial flood, scour and coastal flood).

First, the variables are organized in an event tree, whose structure is based on the event types that are defined in the INFRARISK overarching methodology, namely source events, hazard events, infrastructure events and network events. Following a discussion on the uncertainty sources and the deterministic or probabilistic nature of each variable, a Bayesian Network formulation is also adopted for each hazard type, in order to emphasize the logical relations between variables.

Finally, the Bayesian Networks allow for the identification of which variables may be instantiated by the user, depending on the objectives that are pursued by the risk analysis. For each possible 'instantiation level', the list of required variables and models can therefore be updated, so that the corresponding efforts in terms of implementation and computational load in the INFRARISK Decision Support Tool (IDST) can be assessed. The results of this study can then be used to specify the structure of the IDST and the type of risk analysis that will be proposed to the end-user.

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1.0 INTRODUCTION

The risk analysis of a Critical Infrastructure (CI) system that is subjected to multiple hazards requires the specification of all the variables that are involved in the various modelling steps. Based on the harmonisation methodology developed within the INFRARISK project (see deliverable report D4.1; Adey, 2014), for a given hazard type the chain of analysis can be represented as an event tree, which can be decomposed into the following steps (see example in Figure 1):

- **Source event:** an initiating event that may induce a given hazard level. This event can usually be associated with a return period.
- **Hazard event:** this event represents the distributed loadings that may be applied to the CI system, depending on the magnitude of the source event.
- **Infrastructure (or Element) event:** the physical state of the all infrastructure objects composing the CI system, based on the applied hazard event.
- **Network event:** the state of the CI objects in terms of network functionality (e.g. functionality loss, required restoration time, etc.), based on the physical infrastructure events.
- **Societal event:** the direct and indirect consequences of the previous events, in terms of global network performance indicators. This event is not discussed in the present report, since it involves the use of network analysis models that are out of the scope of WP3.

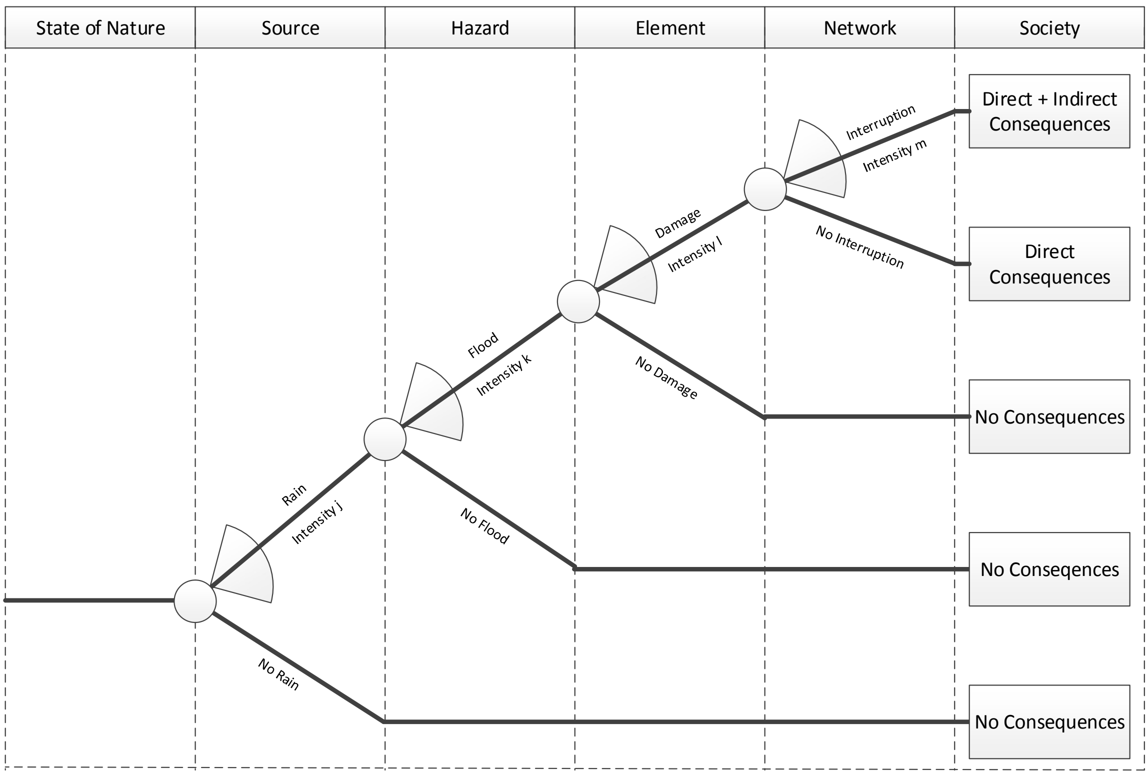

Figure 1: Simplified example of the event-tree structure proposed in INFRARISK deliverable D4.1 (Adey, 2014).

In this report further detail is given to the main parts of each hazard-specific event tree, in order to identify all the variables and modelling choices that take part in the single risk analysis. This step is carried out by using the Hazard Distribution Matrix models that have been developed in detail in INFRARISK deliverable D3.1 (D'Ayala et al., 2014). The visualisation of all variables through an event tree enables a user to intuitively identify the sequence of computations that are required in order to quantify the evolution of the system, from the Source Event to the Network Event.

As proposed by Bearfield and Marsh (2005), the various variables in the event tree can also be represented in the form of a Bayesian Network. Using a simple example, the authors have shown that a Bayesian formulation is complementary to an event-tree representation, since the Bayesian Network enables to focus on the logical relations between variables up to the consequences at the system level. Bearfield and Marsh (2005) have also detailed a set of rules that can potentially reduce the number of edges between event trees and Bayesian Networks:

- *Elimination of consequence arcs:* the consequence arc from a given event can be eliminated if the consequences of its child event(s) are fully explained by the state of the child event(s).
- *Elimination of causal arcs:* the causal arc from an event *i* to an event *j* can be eliminated if the probabilistic outcomes of event *j* do not depend on the state of event *i*.

Once the event trees and Bayesian Networks have been defined with all the variables that are involved in each single risk analysis (see Sections 3 to 7), a rationale is then proposed on the nature of each variable: the Bayesian Networks can be further reduced by only keeping the probabilistic variables (i.e. the variables that are assumed to be associated with uncertainties, as opposed to variables that are the direct outputs of deterministic models). A further distinction can also be made between the Bayesian nodes that can be instantiated (e.g. instantiation by evidence or arbitrary selection by the user) and the ones that result from probabilistic models. Based on this distinction, a decision tree can be then designed, so that the identified instantiable variables can be specified by the user within the INFRARISK Decision Support Tool (IDST), for instance. The remaining variables finally constitute the reduced Bayesian Network, the structure of which depends on the instantiated variables.

2.0 UNCERTAINTY TREATMENT

This section proposes a very brief review on how to account for uncertainty issues in single risk analyses.

2.1 Uncertainty types

Uncertainty sources in risk analyses are commonly detailed within an aleatory or epistemic classification (Wen et al., 2003):

- *Aleatory uncertainties:* they represent the intrinsic variability that is associated with the inherent complexity of the phenomenon to be modelled. The occurrence of earthquake events or the dispersion within the fragility functions (i.e. standard-deviation β) could be considered as examples of aleatory uncertainty, since there will always remain a certain amount of dispersion in the model outcomes, even when all the models/parameters are set as deterministic variables.

- *Epistemic uncertainties:* they are associated with the variability that results from the lack of knowledge or information on the phenomenon to be described. Usually, epistemic uncertainties are found when there is not enough knowledge (e.g. field measurements, parameter characterisation, etc.) to define deterministic input variables.

It should be noted that the aleatory / epistemic classification is somewhat artificial, in the sense that it is highly dependent on the type of model that is used. If a model is developed which includes a large number of parameters to describe a given phenomenon the associated aleatory uncertainty may be reduced and translated into epistemic uncertainties. An example is the use of multivariate fragility functions with respect to seismic hazard. While a mono-variate fragility curve (e.g. use of a scalar intensity measure – IM – such as peak ground acceleration – PGA – to represent the ground motion) may be associated with a large aleatory uncertainty (i.e. high standard-deviation β), the use of a fragility function with a vector IM (e.g. spectral acceleration – Sa – at different periods) is likely to reduce the aleatory uncertainty (i.e. the ground motion is better described), even though the characterisation of the input IMs may be the source of additional epistemic uncertainties.

Finally, the definition of epistemic uncertainties remains rather broad and some authors (e.g. Rohmer, 2013) have introduced more specific sub-categories, such as *data*, *scientific*, *model* and *parameter* uncertainties. In the present report, special care is given to:

- *Model uncertainties:* they are associated with the selection of the different models that are usually available, when describing a given phenomenon (e.g. various fragility curves may be used for the same typology of a CI element). They are usually distributed over a discrete distribution of categorical variables.

- *Parameter uncertainties:* they are associated with the lack of knowledge on the input parameters of the models, resulting from incomplete information on the various environmental variables. These variables can be associated with either a discrete or a continuous distribution

2.2 Uncertainty quantification and propagation

Once the various sources of uncertainties have been identified, they need to be associated with a set of probabilistic distributions: the variability of the uncertain sources can be expressed through many forms, such as analytical probabilistic density functions, empirical distributions or expert-based weighting coefficients.

The final uncertainty (i.e. the dispersion of the chosen loss metric at the end of the risk analysis) can be quantified by estimating how the input uncertainties propagate up to the final analysis step. Therefore the goal is to generate a probabilistic distribution of the final loss metric, based on the initial assumptions on the distribution of the input variables (i.e. choice of models and parameters) and the associated aleatory uncertainties (see Figure 2).

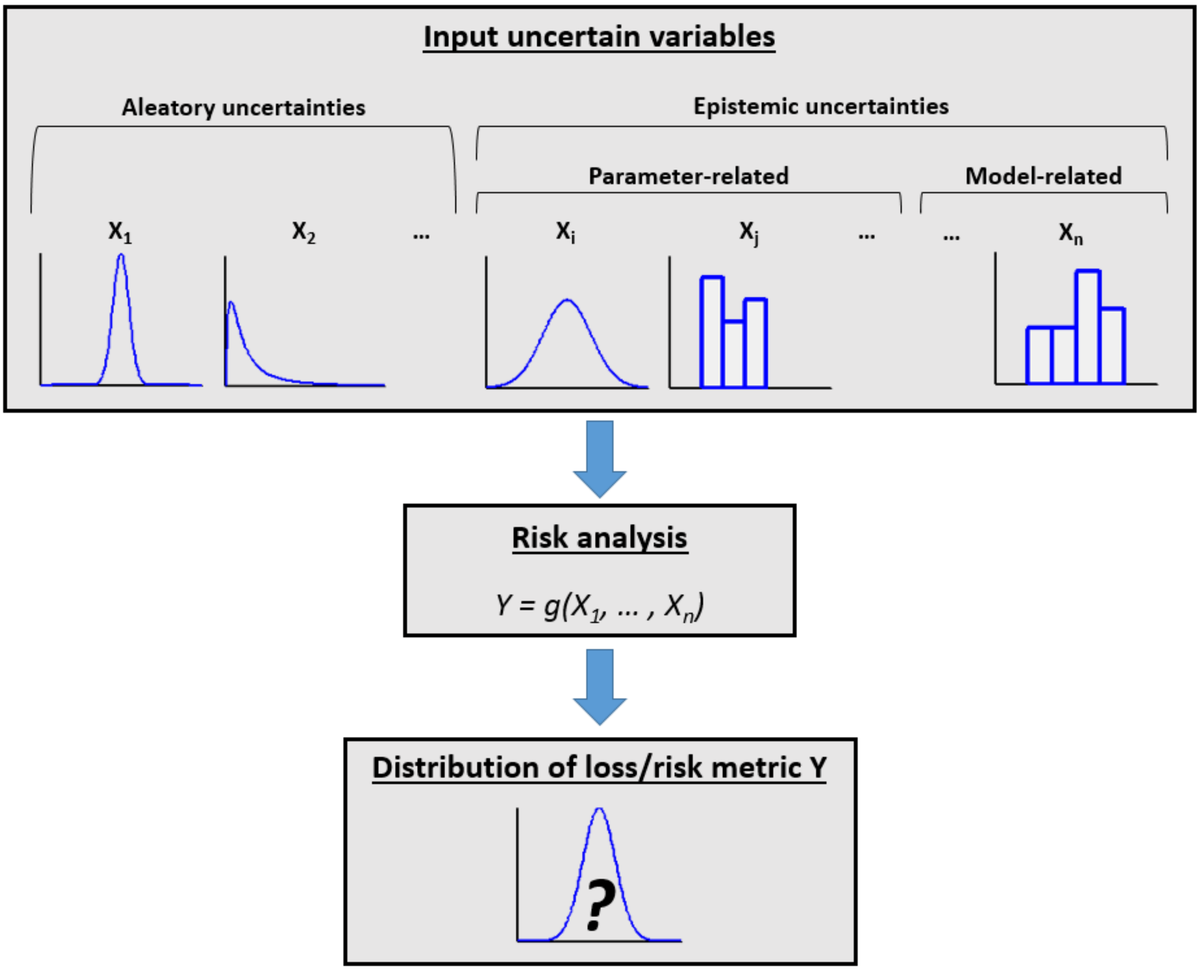

Figure 2: General principle of uncertainty propagation.

In theory, uncertainty propagation could be performed through an exact analysis, as mentioned by Wen et al. (2003), by integrating the joint probability density function of all uncertain variables over the whole space of solution. However, such an approach is not feasible in practice, except for linear cases with independent variables. The possibility of using Second Moment or First-Order Second Moment analyses is also detailed by Wen et al. (2003), but the use of these methods also requires a linearization of the various models, which may not be possible in the complex context of risk analyses. Finally, Monte Carlo simulation techniques are also proposed as a viable alternative to generate numerous random samples of risk outcomes.

Similarly, the review of single-risk uncertainties within the FP7 MATRIX project (Rohmer, 2013) details three possible approaches for uncertainty propagation, namely Monte Carlo simulation techniques, logic trees and Bayesian event trees. Their description will be the object of the sub-sections below.

2.2.1 Monte Carlo simulations

A Monte Carlo simulation consists of the sampling of random realizations of the various input variables and the estimation of the final risk metric for each run. After a larger number of runs, a stable estimation of the probabilistic distribution of the outcome can be constructed. Even though it is very straightforward in principle, the Monte Carlo approach may require an almost intractable number of runs to achieve convergence, especially when there is a high-dimensionality of input variables or when extreme risk values (i.e. low probability outcomes) have to be sampled.

Such issues have been thoroughly investigated and variance reduction techniques have been proposed in order to reduce the number of required runs. Some of the most common techniques are the following:

- *Latin Hypercube sampling (LHS):* this sampling technique is used to optimize the sampling of variables from multi-dimensional distributions (i.e. simultaneous sampling of *n* various input variables). Each input variable has its value range divided into *m* equally probable intervals, and an optimization technique is used in order to ensure that the *m* MC samples efficiently cover the *n*-dimension space of variables. If *n* = 2, the variable space becomes a square of *m* rows and *m* columns and the LHS algorithm (*Latin Square* in two dimensions) selects samples so that each row and each column is occupied by one and only one sample (see Figure 3).

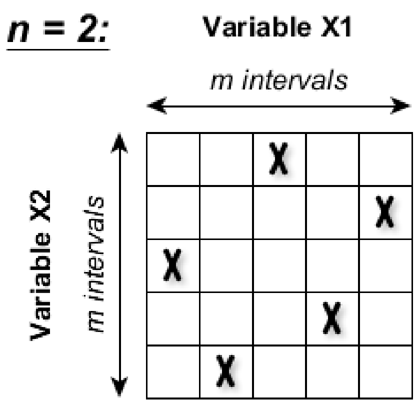

Figure 3: Example of Latin Hypercube sampling in a two-dimension case.

- *Importance sampling (IS):* this sampling approach alters the original distribution of the input variable, in order to preferably sample values of interest that would have a very low probability of being sampled otherwise. For instance, if an input variable is associated with a normal probabilistic distribution and if the upper tail of the distribution is of specific interest for the outcome, importance sampling can be used to ensure that the input variable is sampled following a uniform distribution, for instance, thus artificially raising the proportions of extreme value samples in the MC runs. As a result, the outcome from each run will also have to be weighted when estimating the final statistics, based on the ratio between the original density probability and the one that has been used in the IS. While this approach is very useful to efficiently explore low probability combinations, it requires an *a priori* knowledge of what are the input variables' ranges of interest, with respect to the final outcome.

- *Adaptive sampling (AS):* this sampling method consists in the updating of the sampling scheme based on the results of the previous runs. For instance, specific ranges of input variables could be further investigated, if the previous MC runs have demonstrated a high dependency of the outcomes on a given range of sampled variables.

Finally, it should be noted that Monte Carlo simulation techniques are especially suitable for complex systems with non-linear behaviour, while being able to treat all types of uncertainties (i.e. both aleatory and epistemic).

2.2.2 Logic trees with Monte Carlo simulations

Logic trees are an efficient way to represent and model epistemic uncertainties: more specifically, *model*-related epistemic uncertainties are very commonly represented with logic trees, since the associated variables have a discrete or categorical distribution. A logic tree starts from a source point and branches out into various options (i.e. different models) over several level depths, from a generic problem definition down to very specific details (see Figure 4).

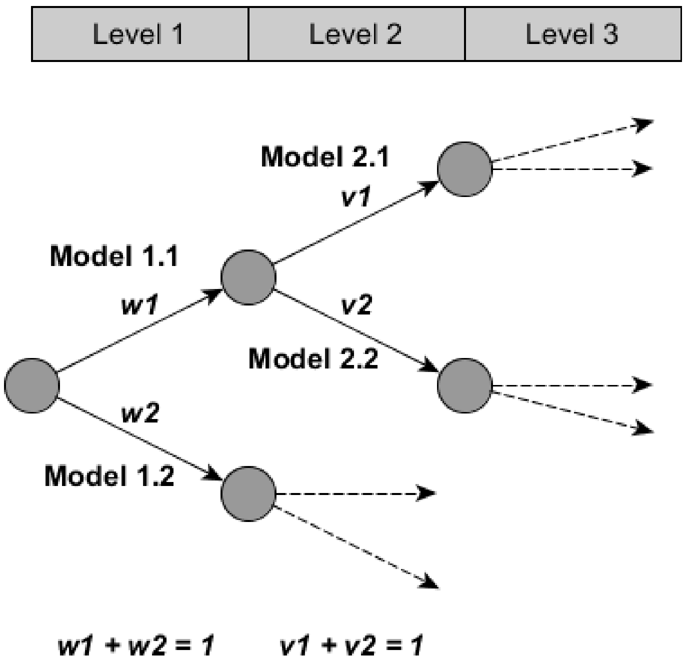

Figure 4: Example of a logic tree structure.

For instance, logic trees have been used to propagate model uncertainties in probabilistic seismic hazard assessment, through the selection of different ground motion prediction equations – GMPEs (Delavaud et al., 2012). In a logic tree, each branch is associated with a weight, which is usually estimated through an expert-elicitation process. The same type of logic tree could also be used for fragility assessment, where different fragility models could be weighted for a given typology.

Once model uncertainties are represented on the logic tree branches with their respective weights, the remaining epistemic uncertainties (i.e. *parameter*-related) as well as the aleatory uncertainties can be propagated by running MC simulations for each branch of the logic tree. The final probabilistic distribution of the outcome metric is then obtained via a weighted sum of the results over all the branches (i.e. the branch weights are used as a probability). For this reason, one important constraint is that logic tree branches must be mutually exclusive and collectively exhaustive (MECE), as stated by Bommer & Sherbaum (2008).

2.2.3 Bayesian Event Tree

Bayesian event trees (BET) have been introduced by Marzocchi et al. (2004, 2010) for probabilistic volcanic hazard assessment and eruption forecasting. They are similar to logic trees in structure (i.e. graphical representation of a tree structure with branches, see Figure 5), however they do not serve the same purpose and they contain fundamental differences with respect to logic trees:

- BETs focus on *events* (and not just model choices, like in logic trees): each branch represents a logical step that ensure the transition from an anterior event to a subsequent event, so that the entire risk analysis can be represented by a chain of intermediate events and outcomes up to the final outcome.
- BETs are based on conditional probabilities and Bayesian theory, in the sense that the probability of event *n* occurring is expressed as the probability of event *n* given event *n-1* has occurred, and so forth.
- Each branch of the BET is associated with a conditional probability, and not just a weighting coefficient like in logic trees. Therefore the MECE assumption is not a prerequisite for BETs.

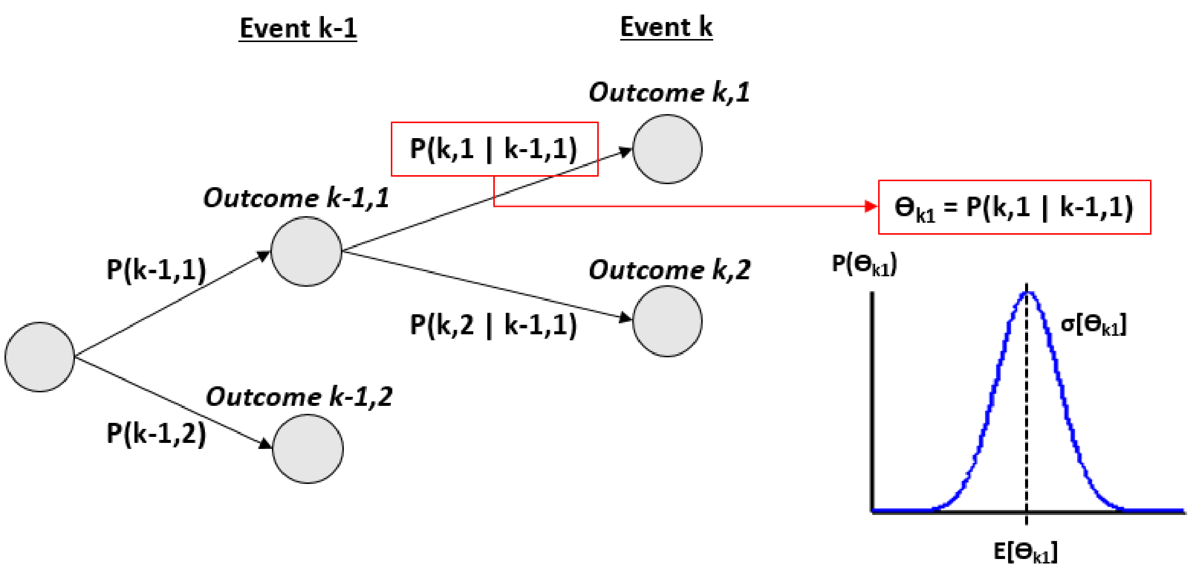

Figure 5: Example of a Bayesian event tree structure with uncertain event probabilities.

One of the most notable BET functionalities featured in Marzocchi et al. (2004) is the way the conditional probability is defined for a given event *k*: this event probability $p(\text{Event}_k \mid \text{Event}_{k-1}) = \Theta_k$ is not necessarily a single scalar value, as it can also be associated with uncertainties that represent the difficulty to accurately quantify each event probability, due to lack of knowledge or field evidence. Therefore each event probability Θ_k can be associated with a probabilistic distribution (i.e. also referred to as a 'probability of probability', see Woo, 1999):

- The average $E[\Theta_k]$ can be seen as the probability due to aleatory uncertainties (i.e. the pure randomness of the process predicting the event *k*).
- The standard deviation $\sigma[\Theta_k]$ of the distribution of Θ_k represents the level of uncertainty that is associated with the estimation of event probability Θ_k: it can be considered as the epistemic uncertainty, i.e. the variability due the lack of knowledge on the models and parameters to be used.

Marzocchi et al. (2004) proposed a Bayesian updating process, based on empirical or historical data, in order to refine the prior distribution of Θ_k: the addition of actual observations enables one to obtain a posterior distribution of Θ_k with a greatly reduced standard deviation $\sigma[\Theta_k]$. Therefore BETs could be used to represent both aleatory and epistemic uncertainties. The distribution of Θ_k is obtained by sampling the various model- and parameter-related uncertainties, while aleatory uncertainties are represented by the expected value of Θ_k. Finally, with the probabilistic distribution of Θ_k defined for each branch of the BET, the conditional probabilities can be sequentially computed in order to estimate the distribution of the final loss metric, which will contain both aleatory and epistemic uncertainties.

2.3 Sensitivity analysis

When a large number of input variables are associated with various uncertainties, the amount of mathematical constructions and computations that are needed to propagate all uncertainties can soon become intractable. To this end, sensitivity analyses usually constitute an efficient way to identify the role of the different uncertainty sources. According to Rohmer (2013), sensitivity analyses can be used to:

- Identify which input factors contribute most to the output uncertainty.
- Identify which input factors are insignificant and can then be eliminated to reduce the dimensions of the problem.
- Determine which input factors interact with each other.

The simplest way to assess the influence of the various uncertainty sources consists in changing one input variable at a time (i.e. "one-factor-at-a-time" analysis). However this approach does not lead in the identification of the interactions between factors and it is only valid in the case of a linear problem.

Another way to perform a sensitivity analysis is the First-Order Reliability Method (FORM), since the sensitivity factors of each input variable are a by-product of the reliability analysis. However FORM analyses usually require closed-form and linearized models with normally distributed variables.

Whilst numerous computation strategies have been developed in order to bypass these limitations, their application to complex nonlinear problems remains cumbersome.

Finally, variance decomposition (i.e. computation of Sobol' indices) provides the most informative sensitivity analysis, while being applicable to any kind of problem. The variance-based global sensitivity analysis (GSA) detailed by Saltelli et al. (2008) enables one to provide the main and total effects associated to each source of uncertainty. The main effects (i.e. first-order contributions of each parameter, without accounting for interaction terms) can be used to individually rank the various sources of uncertainties, while total effects (i.e. second-order indices including contributions from interaction terms) should be used to identify negligible parameters (i.e. input factors with a low main effect and low interactions with other terms) and to measure the level of complexity of the studied problem (i.e. high differences between total and main effects imply a high degree of interaction between the uncertainty sources).

An interesting feature of the variance-based global sensitivity analysis is its ability to combine various types of input factors (i.e. uncertain variables with either continuous or discrete distributions). The estimation of the Sobol' indices (i.e. total and main effects) may be carried out through various algorithms, such as the Monte-Carlo-based Sobol' algorithm (Saltelli, 2002): even though this approach is the most complete and the most versatile form of sensitivity analysis, the associated Monte-Carlo simulations require a large number of model evaluations. Gehl et al. (2013) applied variance-based global sensitivity analysis to the case of uncertainty ranking for seismic risk scenarios. The large number of intensive model computations led to the development of surrogate meta-models in order to reduce the computational load. A similar approach has also been used by Rohmer et al. (2012) for the comparison of the influence of model-related uncertainties against parameter-related uncertainties in earthquake loss assessment procedures.

3.0 EARTHQUAKES

This section details how the various variables and models have to be formalized in order to perform the seismic risk analysis within the IDST.

3.1 Specification of the event tree

The following sub-sections specify the contents of the earthquake event tree, according to the structure proposed by the INFRARISK methodology (i.e. distinction between source, hazard, infrastructure and network events).

3.1.1 Source event

The main variables that are involved in the estimation of the source event are the following (see Figure 6):

- *Regional seismicity:* e.g., activity parameters derived for Europe in the SHARE project, available in the Portal of European Facility for Earthquake Hazard and Risk (EFEHR, www.efehr.org).
- *Return period of interest:* the annual probabilities of interest of ground motion exceedance are needed in order to generate a suitable catalogue of seismic events.
- *Earthquake catalogue:* a simulated catalogue of seismic events based on the seismicity of the studied area is determined. This Monte Carlo approach is further described in deliverable D3.1 (D'Ayala et al., 2014).
- *GMPEs:* a set of different GMPEs, with associated relative weights, could be used. Following the proposed approach by Atkinson et al. (2012), a median GMPE could be aggregated, along with its confidence intervals (i.e. lower and upper boundaries).
- *Suite of reference points*: A suitable number of geographical locations (i.e. up to a few dozens) are chosen that represent critical points in the CI system, either due to the vulnerability of the corresponding CI objects, or due to their influence on the network performance.
- *Ground Motion catalogue:* A simulated catalogue of spatially distributed ground motions based on the catalogue of earthquake events and the selected GMPE models is used. The ground motions are computed for a set of predefined geographical locations (i.e. reference points) and their values correspond to a given percentile level, based on the possible distribution of ground motions at each location, for the given return period. The outcome is therefore a probabilistic map of ground motions, for a given return period at a given percentile level.
- *Reference point:* selection of an anchor point is made from among the locations where the ground motions have been computed. The deterministic shakemap that corresponds to the GM value at the reference point is then used to represent a spatially consistent ground motion field.

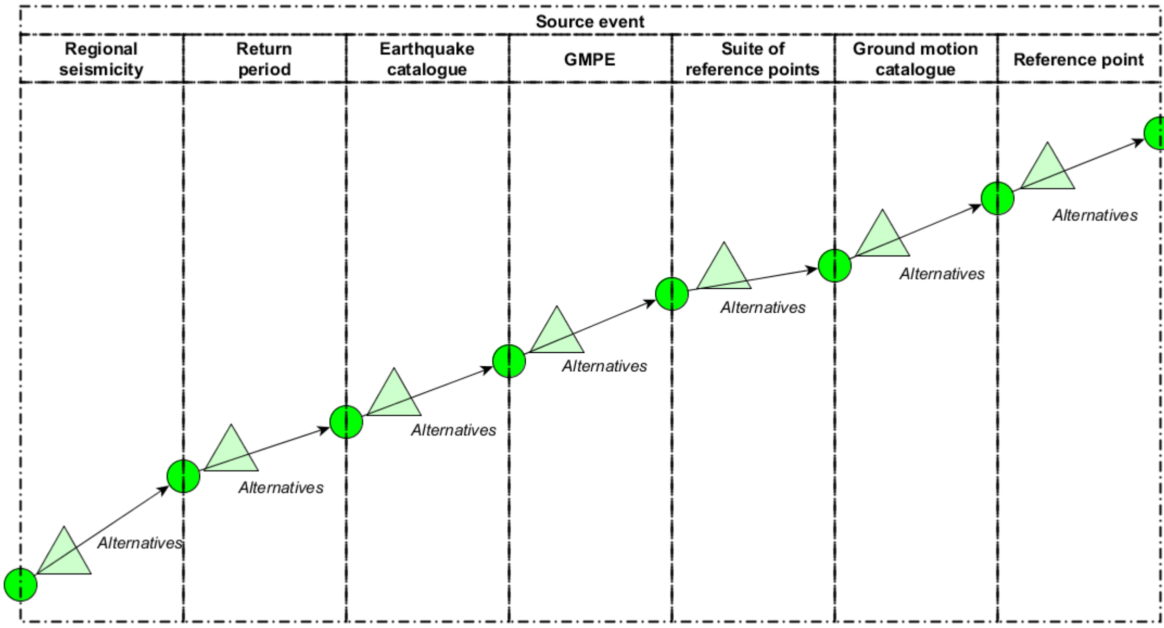

Figure 6: Source Event-tree structure for earthquakes.

3.1.2 Hazard event

The main variables that are involved in the estimation of the hazard event are the following (see Figure 7):

- *Geographical coordinates of the CI element:* longitude and latitude representing the location of the object of interest. A proxy may have to be used, depending on the type of CI element considered (e.g. bridge, tunnel, road segment, slope), which could be described as a point, a line or a polygon (area).

- *Type of IM:* suitable intensity measure for the CI element (e.g. PGA, PGV), which may impact the choice of GMPE and its related uncertainties, as well as the spatial correlation.

- *IM_rock (x,y):* the spatially distributed intensity measure at the site of interest, for a rock site (no soil amplification). IM_rock values are computed for all the geographical locations that correspond to the coordinates of the CI elements.

- *Soil conditions:* local conditions at the site of the CI elements. Soils conditions can be integrated as a GMPE parameter, using soil classes (e.g. EC8 or NEHRP classification, see Appendix A) or Vs30 values. This parameter enables to ensure the transformation from the hazard at rock site (IM_{rock}) to the local hazard (IM_{local}).

- *IM_local (x,y):* the spatially distributed intensity measure at the site of interest, including soil amplification. IM_local values are computed for all the geographical locations that correspond to the coordinates of the CI elements.

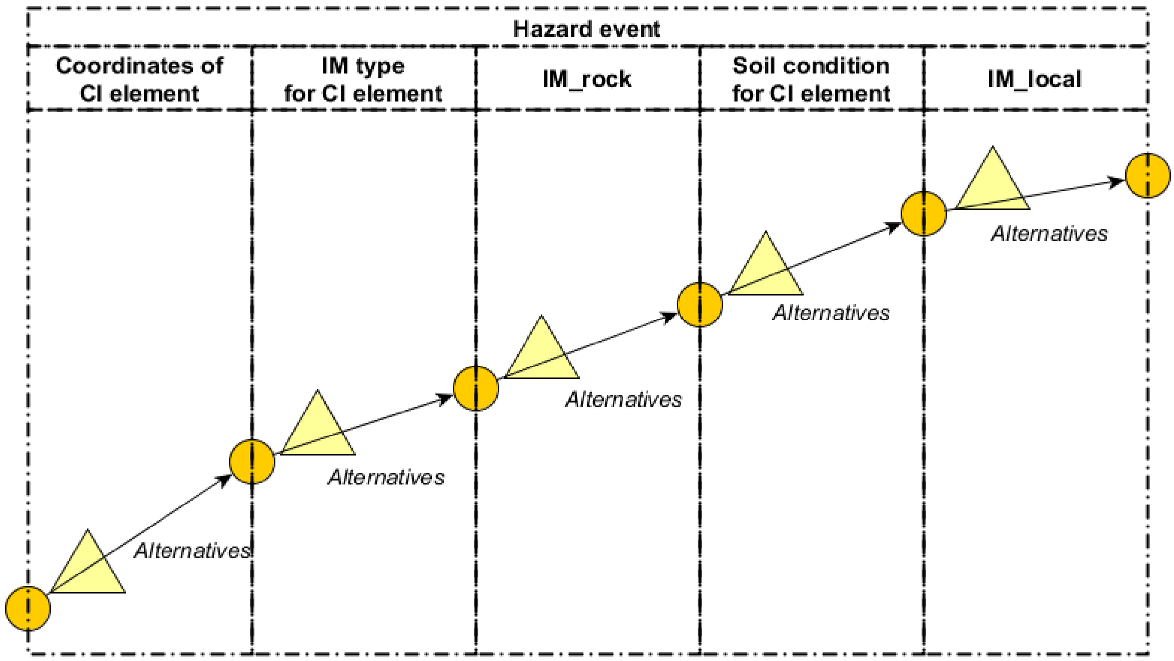

Figure 7: Hazard Event-tree structure for earthquakes.

3.1.3 Infrastructure event

Each CI element is decomposed into its respective structural components, so that fragility curves and damage estimation can be used at the component level.

The main variables that are involved in the estimation of the infrastructure event are the following (see Figure 8):

- *Typology of the CI element*: selection of the structural typology among the proposed classification of the elements at risk.
- *Component within the CI element:* one of the components (e.g. bearing types, abutments, piers) that comprise the CI elements.
- *Component-based fragility curves:* for each component of the CI element, selection of an appropriate set of fragility curves, based on its typology and on the configuration of the CI element.
- *Damage states:* the output of the component fragility curves given the value of IM_local.

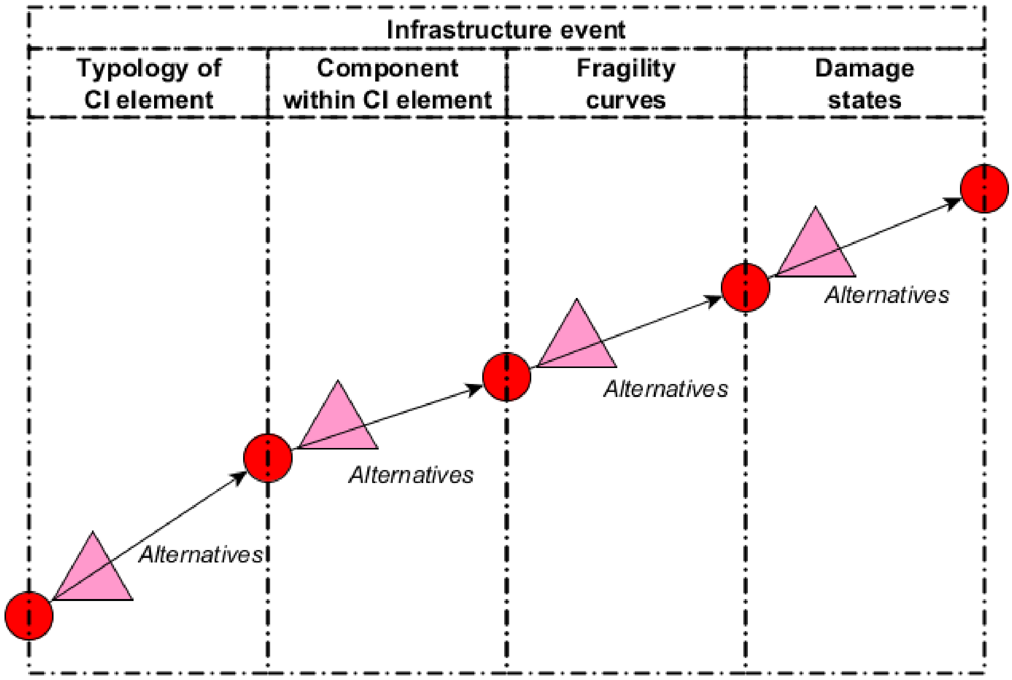

Figure 8: Infrastructure Event-tree structure for earthquakes.

3.1.4 Network event

The "network event" is here referred to as the chain of variables that lead to the estimation of the functionality loss of the physically degraded CI element, in order to enable the computation of the indirect consequences at the network level.

The main variables that are involved in the estimation of the network event are the following (see Figure 9):

- *Functional capacity loss before intervention*: the functional consequences at the level of the CI element of the component damage. Functionality loss metrics could include the following: number of closed lanes, reduction of traffic speed, limitation of traffic type (e.g. closed to trucks, open to emergency vehicles only).

- *Type of intervention*: the type of repair / rehabilitation operations that is required for each specific component damage state.

- *Cost/Duration of intervention*: the cost of intervention can be used to estimate global repair costs of the event (i.e. direct consequences), while the duration of the intervention influences the restoration time (i.e. indirect consequences).

- *Functional capacity loss during intervention*: this is used to represent the effect of the intervention on the functionality of the CI element.

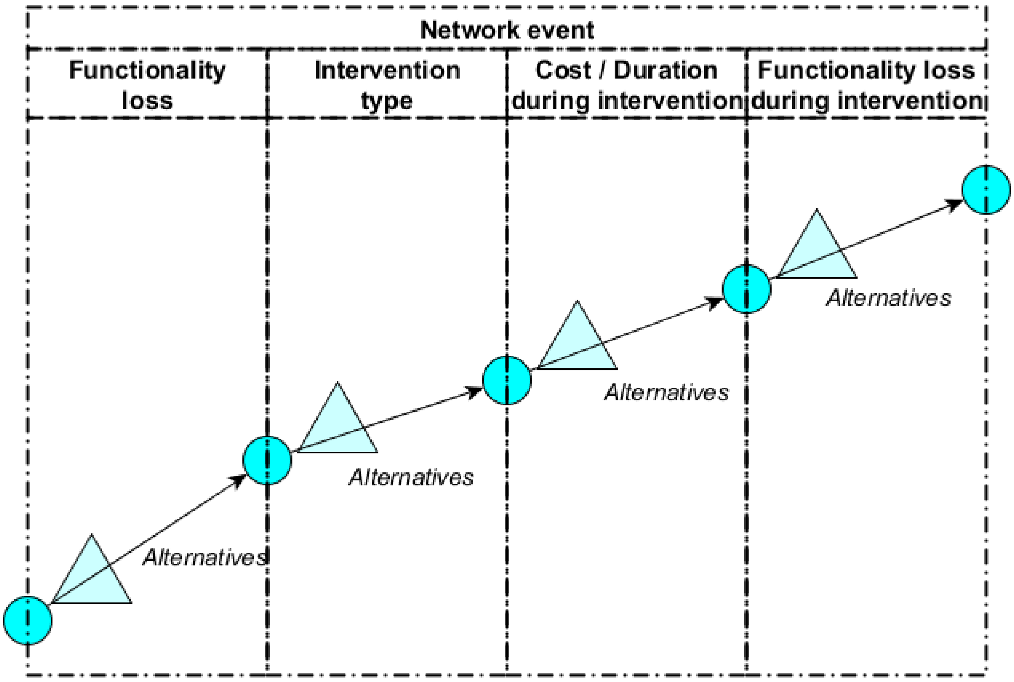

Figure 9: Network Event-tree structure for earthquakes.

Once these variables have been estimated at the component level, they can be aggregated at the level of the CI element, in order to evaluate functionality measures that can be used for the subsequent network analysis. These system-level variables are later referred to as:

- *Functional capacity loss before intervention*;
- *Type of intervention*;
- *Cost/Duration of intervention*;
- *Functional capacity loss during intervention*.

The organization of the variables within the Network event and the relations between component- and system-level functionality measures is summarized below (see Figure 10): however the proposed approach on the estimation of functional losses may still be subject to some changes, pending the results of an expert-elicitation process that has been launched across the INFRARISK project (i.e. quantification of direct/indirect losses corresponding to each component damage state of the CI elements).

The definition of a proper probabilistic distribution for functionality loss and restoration time may not be possible or even applicable in all cases. An alternative could reside in the use of membership functions (i.e. fuzzy logic theory). These functions are well suited to account for the lower and upper bounds of the loss metrics that have been estimated through the expert-elicitation process. Finally, the possible loss values could be implemented into the Bayesian network in order to represent the lack of knowledge on these values.

In Figure 10, some equations have been proposed to aggregate the losses at the element level, based on the estimates of component damage. It is assumed that restoration times can be cumulated over the various repair operations of all damaged components. Regarding functionality losses, it may be expected that the component damage resulting in the highest functionality loss will directly influence the functionality loss at the element level. However, different configurations might also be contemplated, depending on the inner organization of the infrastructure element and the nature of the component damages. Such considerations should be further investigated once the relations between component damage states and functionality losses have been clarified through the expert-elicitation process.

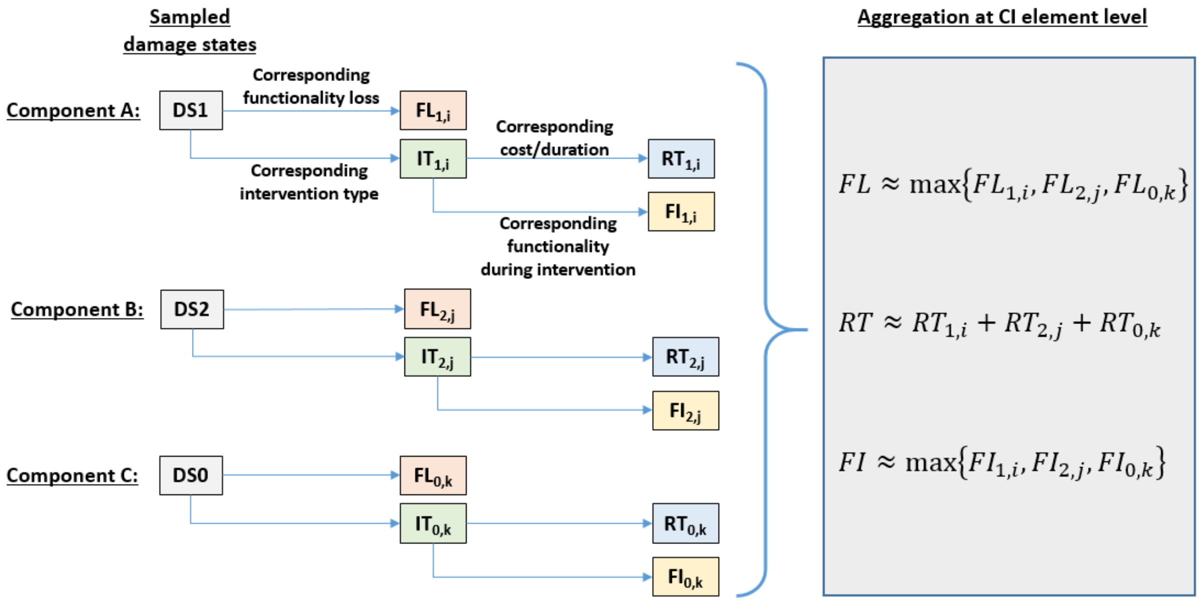

Figure 10: Possible evaluation of functionality variables at the system level, based on the component damage states.

3.2 Uncertainty types

Once the main variables that are involved in the different risk analysis steps have been identified, it is necessary to specify the type of uncertainties they are associated with. A first distinction can be made on whether the variable is of deterministic or probabilistic nature (i.e. whether or not the variable brings additional uncertainty to the computation). In the present study, a variable is referred to as deterministic if it falls into one of the following cases:

- The variable is an input variable to the model (i.e. it does not depend on previous variables) and there is usually little doubt on its actual value. For instance, the geographical coordinates of the CI elements are considered as deterministic variables, since there is no uncertainty on their physical location.

- The variable represents an intermediate outcome of the model (i.e. it is the result of a computation or the combination of previous variables), but the model that leads to its evaluation is purely deterministic. For instance, the selection of the type of intervention based on the damage state may be provided by a correspondence table, and a one-to-one relation between the damage state and the type of intervention is assumed. Even though the damage states have a probabilistic distribution, which implies a probabilistic distribution of the types of intervention, the type of intervention is still considered as a deterministic variable: this convention is adopted in order to stress the fact there will not be any additional uncertainties when the computation moves from the damage states to the types of intervention.

In the case of probabilistic variables, the associated uncertainty can be either aleatory or deterministic (model- or parameter-related), as detailed in Section 2. Variables such as the GMPE type or the element typology could be deterministically defined, if they are assumed to be set-up by the user before the computation. They can also be associated with some variability if required, thus leading to an estimation of the epistemic uncertainties that are due to modelling assumptions. Aleatory uncertainty is present when the variable is the result of a model computation that contains a certain level of randomness: for instance, the distributed IMs are generated through GMPEs that contain a part of aleatory uncertainty. The damage states are also randomly sampled, based on the damage probabilities that are provided by the evaluation of the fragility curves.

The different variables and their corresponding uncertainty sources are summarized in Table 1: this specification exercise is helpful for the construction and the interpretation of the Bayesian Belief Network in the next sub-section.

Table 1: Summary of the main variables and their uncertainties used in the earthquake risk analysis

Event variables	Uncertainty type	Distribution
Source event		
Regional seismicity	Model	Discrete
Return period	Parameter	Continuous
EQ catalogue	Parameter / Aleatory	Continuous
GMPE	Model	Discrete
GM catalogue	Parameter / Aleatory	Continuous
Suite of reference points	Model	Discrete
Reference point	Model	Discrete
Hazard event		
CI coordinates	*Deterministic*	
IM type	Model	Discrete
IM_rock	Aleatory	Continuous
Soil conditions	Parameter	Discrete
IM_local	Aleatory	Continuous
Infrastructure event		
Typology	Model	Discrete
Component	*Deterministic*	
Fragility curve	Model	Discrete
Damage state	Aleatory	Discrete
Network event		
Functionality loss	Aleatory	Continuous
Intervention type	*Deterministic*	
Cost/duration of intervention	Aleatory	Continuous
Functionality loss during intervention	Aleatory	Continuous

3.3 Corresponding Bayesian Network

The event tree detailed above is translated into a Bayesian Network, as shown in Figure 11. All the identified variables are represented as nodes, while the edges are less numerous than all the event-tree relations between the variables. A majority of the links could be eliminated by analyzing the event tree and applying the rules that have been detailed in Section 1 (i.e. elimination of consequence or causal arcs).

This Bayesian Network formulation has been augmented with two types of information that reflect the type of variables that are involved:

- **Deterministic variables:** variables such as the geographical coordinates of the CI elements or the components composing each CI element are directly imposed by the studied area and they are not subject to any uncertainties. Therefore these variables could be removed from the Bayesian network, since they do not contribute to the probabilistic framework: it has been chosen to represent them anyway, in order to emphasize the logical relations between all variables. They are represented in grey in the following Bayesian network.

- **Instantiable variables:** they represent the locations of the Bayesian Network where the Bayesian nodes may be instantiated (i.e. selection of the state of the variable), due to the possibility of gathering empirical evidence or due to the possibility for the user to arbitrarily select a given state. While all variables within the BN can be instantiated in theory, the decision whether a variable may be instantiated or not in the present case results from an analysis of the usual 'entry levels' of the different types of risk analyses (e.g. full probabilistic study vs single scenario simulation).

Depending on the position of the instantiated variable in the Bayesian Network, different 'instantiation levels' can be defined, each one of them bearing a different meaning in terms of risk analysis objectives (see next sub-section for more details).

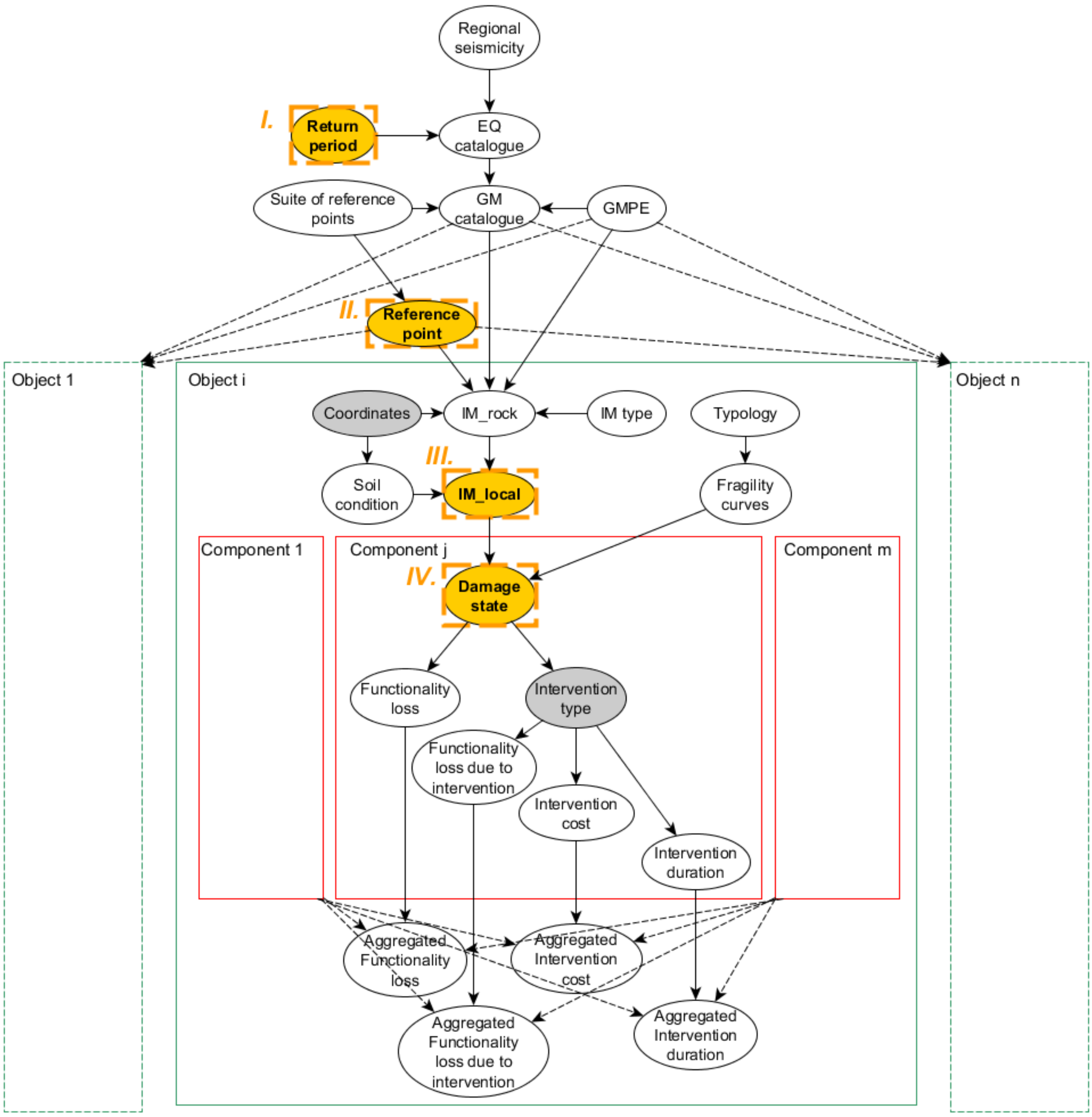

Figure 11: Bayesian Network structure for earthquake risk. The grey nodes represent the variables that can be assumed as deterministic and/or directly imposed by the state of the environment. The nodes within the dashed orange frame represent the variables that may be instantiated by the end-user (i.e. instantiation levels).

This Bayesian Network should be put in perspective with previous Bayesian Networks that have been proposed in several studies for the generation of seismic risk scenarios for spatially distributed systems (Bensi et al., 2011; Franchin and Laura, 2014). In the present study, for simplification purposes, the uncertainties associated with the GMPEs (i.e. intra- and inter-event errors ε and η) are not displayed: however they are implicitly present in the 'IM_rock' node, which is associated with aleatory uncertainties (see Table 1). The spatial correlation structure that is used for the estimation of spatially distributed IMs has also to be taken into account, as well as the correlation structure between damage events at component level.

It is planned to detail the analysis of these uncertainties in INFRARISK deliverable D3.3, which is entirely devoted to the application of Bayesian Networks for the quantification of uncertainties associated with each single risk.

3.4 Corresponding decision tree for the IDST

The Bayesian Network in Figure 11 identifies four instantiation levels, which can be detailed as follows:

- **Level I:** the return period is instantiated (i.e. selection of a given return period of interest), which means that the rest of the analysis will generate risk outputs for the same return period.
- **Level II:** the reference point is instantiated for a given return period (i.e. selection of a spatially and temporally consistent hazard distribution, based on the value found at a selected site of interest), which means that the rest of the analysis will be performed for the same single event.
- **Level III:** the distribution of the locals IMs at all sites of interest is instantiated (i.e. direct use of a shake-map as input for all objects 1...n), which means that the rest of the analysis will be performed for the same level of hazard.
- **Level IV:** the component damage states of all CI elements are instantiated (i.e. definition of the physical state of the components of all objects 1…n), which means that the rest of analysis will focus on the functional consequences of a given physical disruption of the CI system.

Based on this rationale, a decision tree can be defined in order to guide the IDST user on which variables to consider for each chosen level of instantiation (see Figure 12). In the present context, the Bayesian inference is only used in order to facilitate a forward analysis (i.e. estimation of the probability distribution of the child nodes). Therefore, once a given node has been instantiated, only the downstream part of the Bayesian Network is of interest. As a result, only the variables that are needed to estimate the direct/indirect consequences when starting from the instantiated node are represented in Figure 12.

The actual Bayesian Networks (i.e. without deterministic variables and instantiated nodes) corresponding to the different analysis levels are represented in Appendix B.

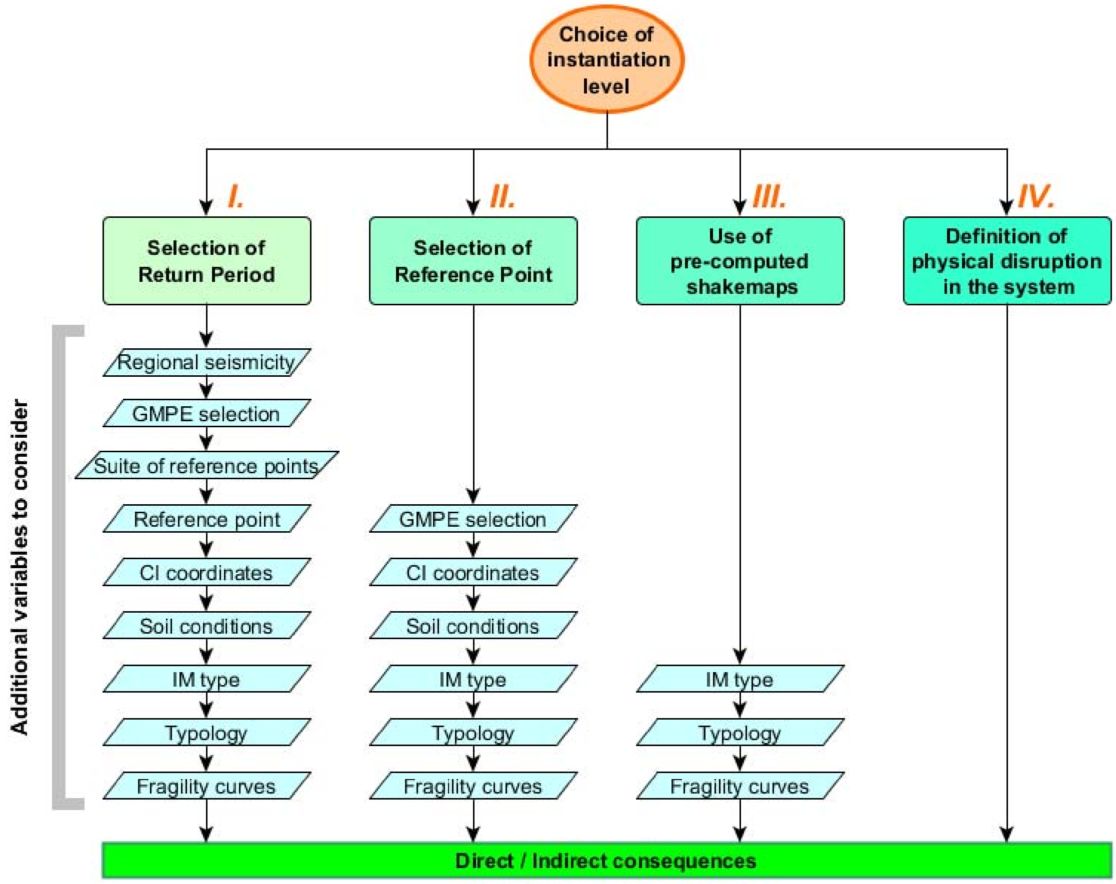

Figure 12: Decision tree for the earthquake risk analysis within the IDST.

3.5 Recommendations for the IDST structure and models

The analysis levels defined in Figure 12 are associated with different levels of complexity and computational load: for instance, the assessment of all probabilities deriving from level *I* does not seem feasible within the IDST, due to the large number of variable samplings and model evaluations that would be required. However, the execution of levels *II* to *IV* is reasonable within the IDST, as long as the tasks and models detailed in Table 2 can be implemented.

Table 2: Models and data sets that are required in the IDST for each considered analysis level

Analysis level		Models and data
Level II	**Input data**	**- GM catalogue:** • Generated off-line for a given return period and a given seismicity level, for the suite of pre-defined reference points; • Embedded within the IDST; • No action needed from the IDST user; **- GIS file of CI elements:** • Shapefile embedded within the IDST; • Possibility for the IDST user to select a specific geographical area (i.e. subset of the original shapefile);

		- GIS file of soil classes (e.g. EC8/NHERP classification): • Generated by the project team / use of a map from an external source; • Embedded within the IDST; • No action needed from the IDST user; **- One reference point among the suite of reference points:** • Selection by the IDST user; • Selection could be done by clicking on the reference point on the map of the CI elements; **- IM of interest (e.g. PGA, PGV, SA):** • Selected by the IDST user via a drop-down menu; • Possible choices (e.g. PGA, SA(T), PGV) should only be proposed if the GM catalogue and the fragility curves are available for these specific IMs; **- GMPE of interest (selection among a few references)** • Selected by the IDST user via a drop-down menu; • Possible GMPEs are either extracted from the literature or developed within the project (i.e. composite GMPEs derived following to the approach by Atkinson et al., 2012); • Possible GMPE models have to be coded within the IDST;
	Computations / Operations	- use of the GMPE model to compute distributed IM_local values at the locations of the CI elements; - aleatory uncertainties associated with the GMPE model could be used to sample different IM_local outcomes;
Level III	**Input data**	**- GIS file of IM_local values at the locations of the CI elements (i.e. outcome of level II):** • Deterministic skake-map generated by CSIC for a given return period, a given seismicity level and a given reference point; • Embedded within the IDST; • No action needed from the IDST user; **- typology of the CI elements and corresponding structural components (i.e. attribute table in the GIS file):** • Typology could be directly embedded in the IDST , e.g. through an attribute table in the GIS file of the CI; • The IDST user could also be given the choice to associate each CI element with a typology through a drop-down menu; • In all cases, a taxonomy of typologies of CI elements should be implemented into the IDST; **- catalogue of fragility functions:** • Database of fragility functions that are either extracted

		from the literature or developed within the project; • By default, a correspondence table (i.e. typology <-> fragility curves) will ensure that the different typologies can be associated with the fragility curves; • The IDST user could also be given the choice to propose a user-defined correspondence table (e.g. through a set of drop-down menus);
	Computations / Operations	- for each component, choice of a set of fragility functions given the typology (i.e. correspondence table between typologies and fragility functions); - computation of the component damage probabilities with the fragility model and the IM_local value; - random sampling of the component damage states (i.e. use of a standard uniform variable to sample a given damage state out of the damage probabilities);
Level IV	**Input data**	**- component damage states for all CI elements (i.e. outcome of level III):** • Using the shapefile of the CI elements, the IDST user could click on the various elements and impose different damage states on their respective components; • The outcome would be a deterministic damage map that could be used to estimate the induced direct and indirect losses; **- correspondence table between component damage states and functionality losses (with or without uncertainties on the values):** • By default, a correspondence table (i.e. component damage state <-> functionality loss) will ensure that the different damage states can be associated with functionality losses; • The correspondence table may be defined with uncertain values (e.g. lower/upper bounds): the IDST user could be given the choice whether to sample these uncertainties or use deterministic values; • The IDST user could also be given the choice to propose a user-defined correspondence table (e.g. through a set of drop-down menus); **- correspondence table between component damage states and intervention types:** • By default, a correspondence table (i.e. component damage state <-> intervention type) will ensure that the different damage states can be associated with intervention types; • The IDST user could also be given the choice to propose a user-defined correspondence table (e.g. through a set of drop-down menus);

	- correspondence table between intervention types and cost/duration (with or without uncertainties on the values): • By default, a correspondence table (i.e. intervention type <-> cost/duration) will ensure that the different intervention types can be associated with costs/durations; • The correspondence table may be defined with uncertain values (e.g. lower/upper bounds): the IDST user could be given the choice whether to sample these uncertainties or use deterministic values; • The IDST user could also be given the choice to propose a user-defined correspondence table (e.g. through a set of drop-down menus); **- correspondence table between intervention types and functionality losses during intervention (with or without uncertainties on the values):** • By default, a correspondence table (i.e. intervention type <-> functionality loss during intervention) will ensure that the different intervention types can be associated with functionality losses; • The correspondence table may be defined with uncertain values (e.g. lower/upper bounds): the IDST user could be given the choice whether to sample these uncertainties or use deterministic values; • The IDST user could also be given the choice to propose a user-defined correspondence table (e.g. through a set of drop-down menus);
Computations / Operations	- determination of functionality loss based on component damage state (use of correspondence table + sampling on the uncertainties if available) - determination of intervention type based on component damage state (use of correspondence table) - determination of intervention cost and duration based on intervention type (use of correspondence table + sampling on the uncertainties if available) - determination of functionality loss during intervention based on intervention type (use of correspondence table + sampling on the uncertainties if available) - aggregation of losses/costs/repairs from the component-level to the CI element-level

4.0 LANDSLIDES

This section details how the various variables and models have to be formalized in order to perform the landslide risk analysis within the IDST.

4.1 Specification of the event tree

The following sub-sections specify the contents of the landslide event tree, according to the structure proposed by the INFRARISK methodology (i.e. distinction between source, hazard, infrastructure and network events).

4.1.1 Source event

The main variables that are involved in the estimation of the source event are the following (see Figure 13):

- *Shake-map of earthquake ground-motion:* A distribution of ground-motion parameters (i.e. IMs PGA and PGV, including local site amplifications) in the area of interest. This data is the output of the previous earthquake risk analysis (see above sections).
- *Return period of interest*: the selected return period of the rainfall event.
- *Rainfall pattern:* rainfall intensity and duration over the area of interest.

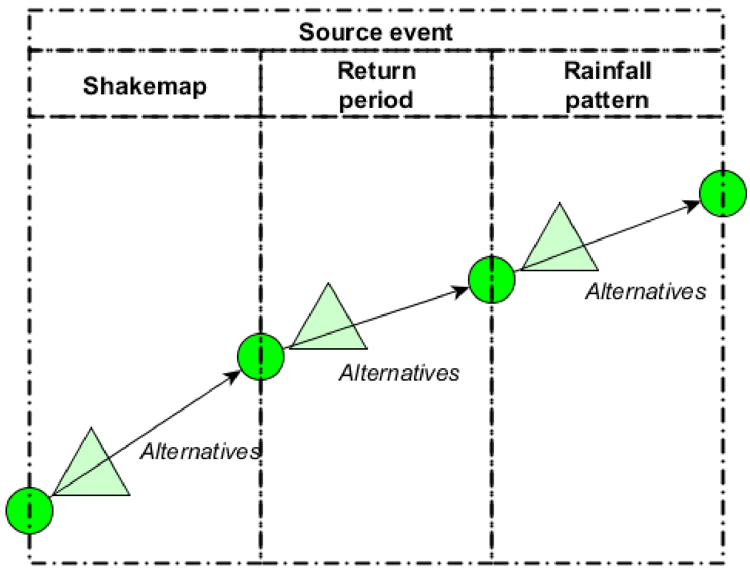

Figure 13: Source Event-tree structure for ground failures.

4.1.2 Hazard event

The main variables that are involved in the estimation of the hazard event are the following (see Figure 14):

- *Geographical coordinates of the CI element:* longitude and latitude representing the location of the object of interest. A proxy may have to be used, depending on the type of CI element considered (e.g. bridge, tunnel, road segment, slope), which could be described as a point, a line or a polygon (area).

- *IM_local (x,y):* the interpolated earthquake intensity measure(s) at the site of the CI element, based on the previously obtained shake map. IM_local values are computed for all the geographical locations that correspond to the coordinates of the CI elements.

- *Digital Elevation Model (DEM):* this model computes the slope angle of the ground that supports the road segment.

- *Slope angle:* the grade of the soil surrounding the CI element of interest.

- *Soil properties:* parameters such as effective cohesion, internal friction angle, unit weight and failure surface thickness are required to quantify the factor of safety (FS) of the slope.

- *Saturation ratio:* this variable is directly linked to the rainfall pattern (i.e. duration and intensity) and to the soil type.

- *Soil yield acceleration (k_y)*: the yield acceleration is expressed as a function of the factor of safety and the slope angle.

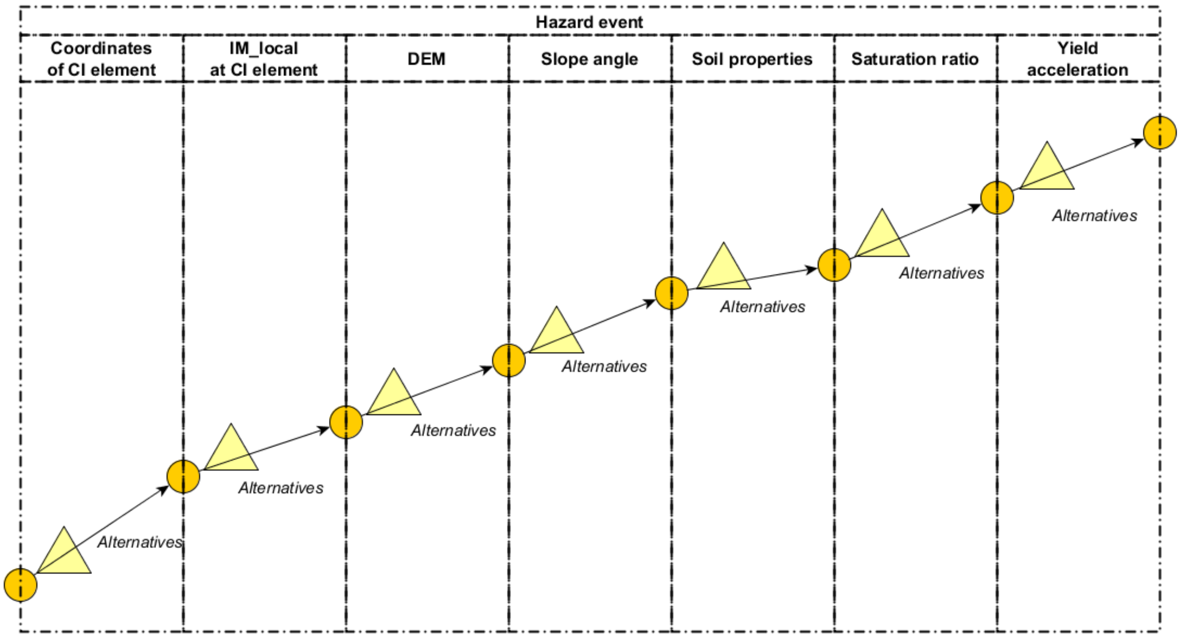

Figure 14: Hazard Event-tree structure for ground failures.

4.1.3 Infrastructure event

Different levels of soil displacement are selected, depending on the type of physical damage they induce to the road or rail segments. Based on these thresholds and on the probabilistic displacement model, landslide fragility curves can be assembled, expressing the probability of reaching or exceeding a given displacement with respect to PGA or [PGA;PGV].

Once the fragility curves have been defined, the Infrastructure Event-tree for ground failures is the same as the one for earthquakes (see Figure 8). The only difference resides in the type of CI elements: in the case of ground failures, road segments are the most exposed and they are comprised of much less structural components than bridges or tunnels. As a result, the component-based decomposition of road segments exposed to ground failures is more straightforward than in the case of bridges exposed to earthquakes.

4.1.4 Network event

The approach is similar to the event tree described in Section 3.1.4, please refer to Figure 9.

4.2 Uncertainty types

The different variables and their corresponding uncertainty sources are summarized in Table 3: this specification exercise is helpful for the construction and the interpretation of the Bayesian Belief Network in the next sub-section. Two important observations have to be made regarding these uncertainties:

- All earthquake-related variables (i.e. shakemap, seismic IM) are considered as fully deterministic, even though they are the result of extensive probabilistic developments, as shown by the BN in Figure 11. Since the scope of the present report is single risk analysis, this section is only concerned with landslide risk and it is assumed that the triggering event (i.e. earthquake event) is kept deterministic for simplification purposes.

- The outcome of the hazard event, i.e. the soil yield acceleration, is considered as deterministic to stress the fact that it is the result of a set deterministic equations. The probabilistic distribution of this variable is actually due to the epistemic uncertainties that are associated with the input parameters (e.g. soil properties or saturation ratio).

Table 3: Summary of the main variables and their uncertainties used in the landslide risk analysis

Event variables	Uncertainty type	Nature
Source event		
Earthquake shakemap	*Deterministic*	
Return period of rainfall	Parameter	Continuous
Rainfall pattern	Parameter / Aleatory	Continuous
Hazard event		
CI coordinates	*Deterministic*	
IM_local	*Deterministic*	
Digital Elevation Model	*Deterministic*	
Slope angle	Parameter	Continuous
Soil properties	Parameter	Continuous
Saturation ratio	Parameter / Aleatory	Continuous
Soil yield acceleration (k_y)	*Deterministic*	
Infrastructure event		
Typology	Model	Discrete
Component	*Deterministic*	
Fragility curve	Model	Discrete
Damage state	Aleatory	Discrete
Network event		
Functionality loss	Aleatory	Continuous
Intervention type	*Deterministic*	
Cost/duration of intervention	Aleatory	Continuous
Functionality loss during intervention	Aleatory	Continuous

4.3 Corresponding Bayesian network

The event tree detailed above is translated into a Bayesian Network, as shown in Figure 15. As for the earthquake case, a distinction is made between deterministic/fixed variables and instantiable variables.

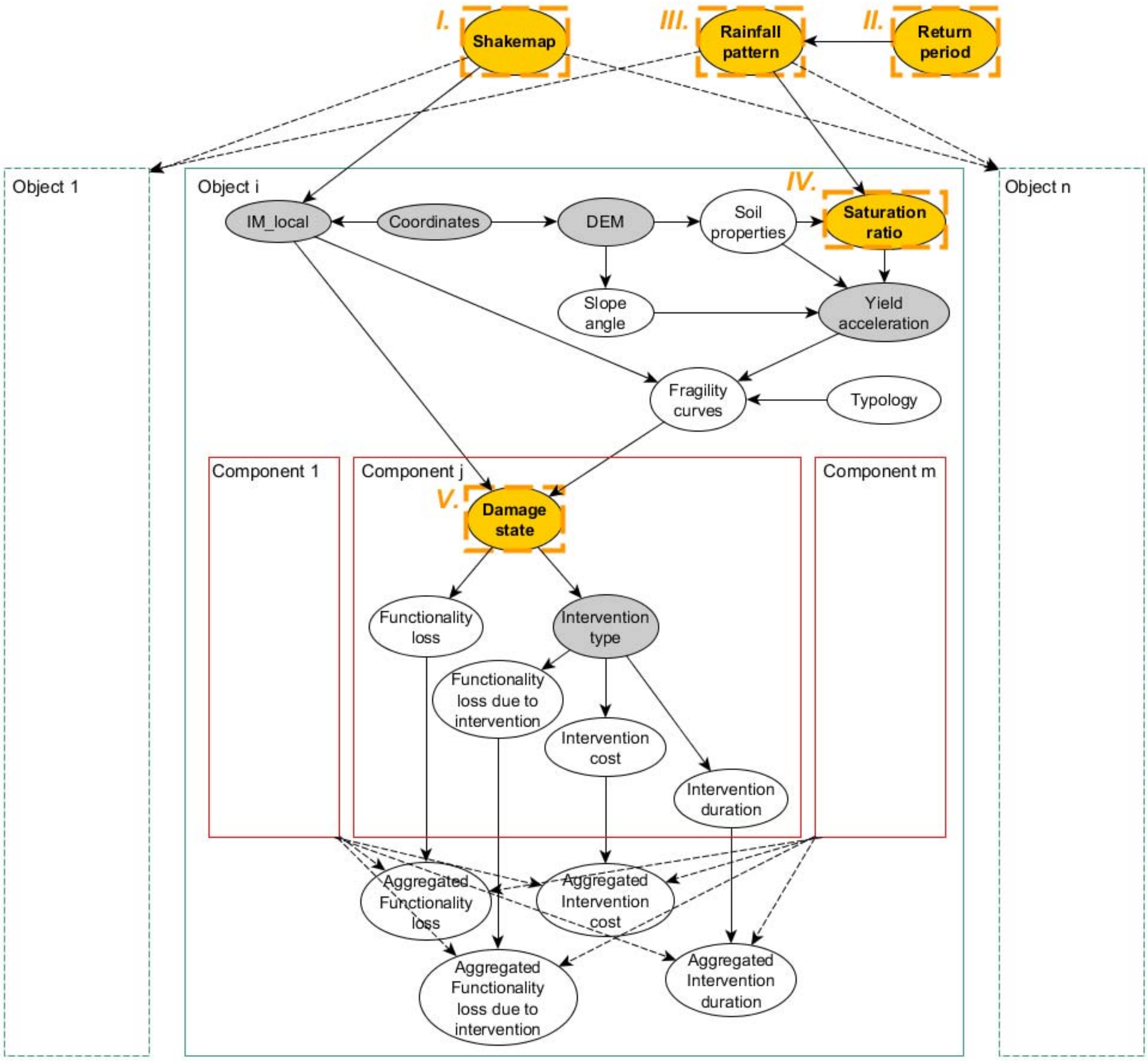

Figure 15: Bayesian Network structure for ground failure risk. The grey nodes represent the variables can be assumed as deterministic and/or directly imposed by the state of the environment. The nodes within the dashed orange frame represent the variables that may be instantiated by the end-user (i.e. instantiation levels).

4.4 Corresponding decision tree for the IDST

The Bayesian Network in Figure 15 allows for the identification of five instantiation levels, which can be detailed as follows:

- **Level I:** the earthquake shakemap is instantiated, which means that the ground failure risk analysis will be performed for a single earthquake hazard event, for any rainfall pattern at any return period.

- **Level II:** the return period is instantiated (i.e. selection of a given return period of interest), which means that the rest of the analysis will generate risk outputs for the same return period.

- **Level III:** the rainfall pattern is instantiated (i.e. selection of a single rainfall scenario with a given pattern of duration and intensity), which means that the rest of the analysis will be performed for the same single event.

- **Level IV:** the saturation ratio at the sites of interest is instantiated (i.e. direct use of saturation ratio maps as input), which means that the rest of the analysis will be performed for the same level of hazard.

- **Level V:** the component damage states of all CI elements are instantiated (i.e. definition of the physical state of the network elements), which means that the rest of analysis will focus on the functional consequences of a given physical disruption of the CI system.

Based on this rationale, a decision tree can be defined in order to guide the IDST user on which variables to consider for each chosen level of instantiation (see Figure 16). It can be observed that the choice of instantiation levels *I* to *IV* does not change the number of input variables to consider. This is due to the nature of the ground failure hazard, whose computation requires extensive information on the soil configuration, even when both earthquake and rainfall hazards are fully specified. However, the Bayesian Network will be dramatically reduced as the instantiation level evolves from *I* up to *IV*.

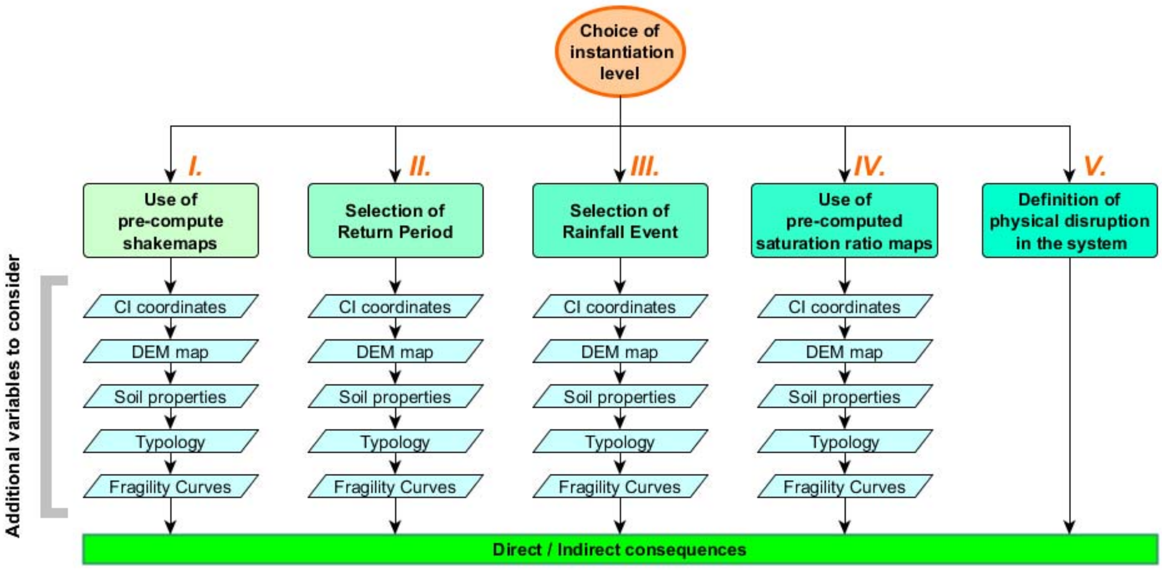

Figure 16: Decision tree for the ground failure risk analysis within the IDST.

4.5 Recommendations for the IDST structure and models

The analysis levels defined in Figure 16 are associated with different levels of complexity and computational load. For instance, the assessment of all probabilities deriving from levels *I* to *III* does not seem feasible within the IDST, due to the large number of variable samplings and model evaluations that would be required. However, the execution of levels *IV* to *V* is reasonable within the IDST, as long as the tasks and models detailed in Table 4 can be implemented.

Table 4: Models and data sets that are required in the IDST for each considered analysis level

Analysis level		Models and data
Level IV	**Input data**	- GIS file of seismic IM_local values at the sites of interest - GIS file of CI elements - GIS file of soil saturation ratios (i.e. may be computed for a few samples of rainfall events) - GIS file of Digital Elevation Model - GIS file of soil properties (e.g. effective cohesion, internal friction angle, unit weight, failure surface thickness) - typology of the CI elements and corresponding structural components (i.e. attribute table in the GIS file) - catalogue of fragility functions
	Computations / Operations	- computation of the factor of safety (deterministic equation) of the slopes surrounding each CI element - computation of the yield acceleration (deterministic equation) of the slopes surrounding each CI element - for each component, choice of a set of fragility functions given the typology and the slope yield acceleration (i.e. correspondence table between typologies and fragility functions) - computation of the component damage probabilities with the fragility model and the IM_local value - random sampling of the component damage states (i.e. use of a standard uniform variable to sample a given damage state out of the damage probabilities)
Level V	**Input data**	- component damage states for all CI elements (i.e. outcome of level IV) - correspondence table between component damage states and functionality losses (with or without uncertainties on the values) - correspondence table between component damage states and intervention types - correspondence table between intervention types and cost/duration (with or without uncertainties on the values) - correspondence table between intervention types and functionality losses during intervention (with or without uncertainties on the values)
	Computations / Operations	- determination of functionality loss based on component damage state (use of correspondence table + sampling on the uncertainties if available) - determination of intervention type based on component

	damage state (use of correspondence table) - determination of intervention cost and duration based on intervention type (use of correspondence table + sampling on the uncertainties if available) - determination of functionality loss during intervention based on intervention type (use of correspondence table + sampling on the uncertainties if available) - aggregation of losses/costs/repairs from the component-level to the CI element-level

5.0 FLOODS

This section details how the various variables and models have to be formalized in order to perform the flood risk analysis within the IDST.

5.1 Specification of the event tree

The following sub-sections specify the contents of the flood event tree, according to the structure proposed by the INFRARISK methodology (i.e. distinction between source, hazard, infrastructure and network events).

5.1.1 Source event

The main variables that are involved in the estimation of the source event are the following (see Figure 17):

- *Return period of interest*: the selected return period of the rainfall event.
- *Rainfall pattern:* rainfall intensity and duration over the area of interest.

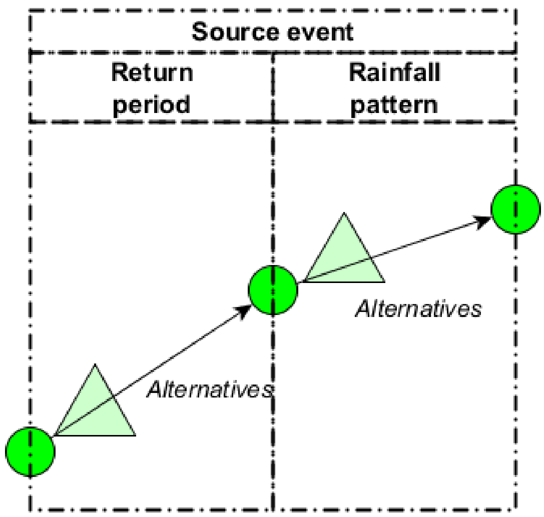

Figure 17: Source Event-tree structure for fluvial floods.

5.1.2 Hazard event

The main variables that are involved in the estimation of the hazard event are the following (see Figure 18):

- *Digital Elevation Model (DEM):* this model allows for the evaluation of the channel slope grade as well as the runoff coefficient.
- *Soil conditions:* these parameters are used to evaluate the runoff coefficient.
- *Runoff coefficient*: the coefficient used in the rational method, usually defined as a function of the soil type (or land use) and the slope grade.
- *Time of concentration (T_c)*: time taken by the rainfall to reach the outlet gauge from the most remote point of the catchment.

- *Geographical coordinates of the CI element:* longitude and latitude representing the location of the object of interest. A proxy may have to be used, depending on the type of CI element considered (e.g. bridge, tunnel, road segment, slope), which could be described as a point, a line or a polygon (area).
- *Channel section:* shape and size of the channel section, in order to estimate the water depth as a function of the flow discharge, at the location of the CI element.
- *IM value (x,y)*: expressed either as water depth or flow discharge ([volume/time]), or both. IM values are computed for all the geographical locations that correspond to the coordinates of the CI elements.

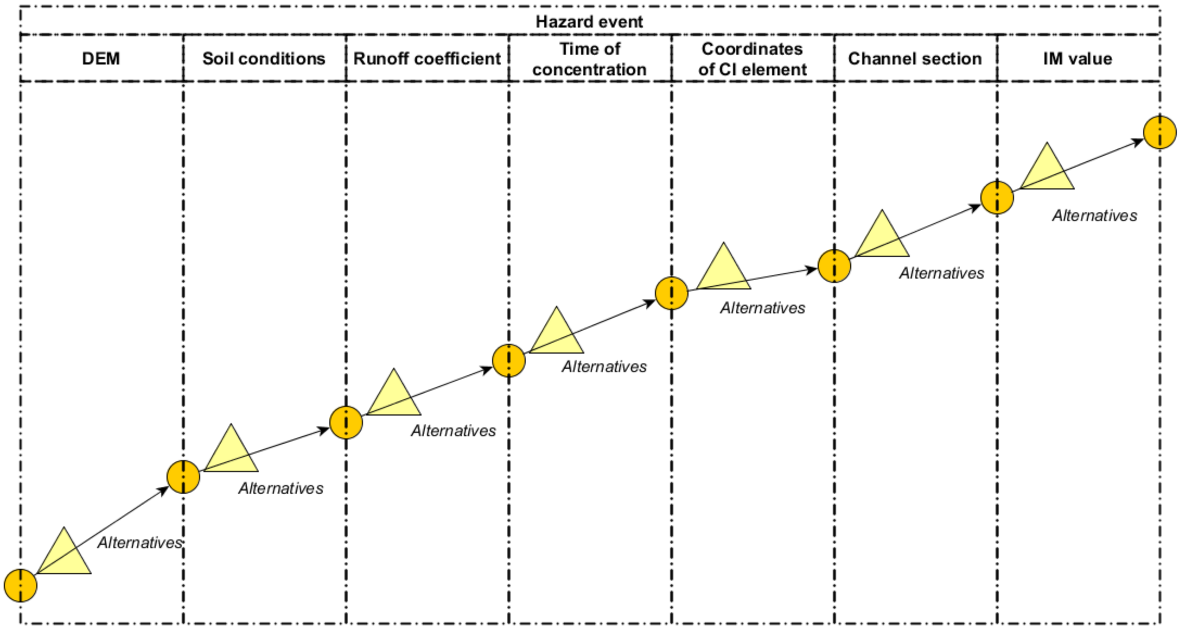

Figure 18: Hazard Event-tree structure for fluvial floods.

5.1.3 Infrastructure event

The Infrastructure Event-tree for fluvial floods is the same as the one for earthquakes, Figure 8.

5.1.4 Network event

The approach is similar to the event tree described in Section 3.1.4, please refer to Figure 9.

5.2 Uncertainty types

The different variables and their corresponding uncertainty sources are summarized in Table 5: this specification exercise is helpful for the construction and the interpretation of the Bayesian Belief Network in the next sub-section. For the landslide risk analysis, the estimation of the flood-related IMs is a deterministic process, while the variability in the IM prediction is introduced by the epistemic uncertainties that are related to the input parameters, such as soil conditions or channel section.

Table 5: Summary of the main variables and their uncertainties used in the flood risk analysis

Event variables	Uncertainty type	Nature
Source event		
Return period of rainfall	Parameter	Continuous
Rainfall pattern	Parameter / Aleatory	Continuous
Hazard event		
Digital Elevation Model	*Deterministic*	
Soil conditions	Parameter	Continuous
Runoff coefficient	Parameter	Continuous
Time of concentration	Parameter	Continuous
CI coordinates	*Deterministic*	
Channel section	Parameter	Continuous
IM value	*Deterministic*	
Infrastructure event		
Typology	Model	Discrete
Component	*Deterministic*	
Fragility curve	Model	Discrete
Damage state	Aleatory	Discrete
Network event		
Functionality loss	Aleatory	Continuous
Intervention type	*Deterministic*	
Cost/duration of intervention	Aleatory	Continuous
Functionality loss during intervention	Aleatory	Continuous

5.3 Corresponding Bayesian network

The event tree detailed above is translated into a Bayesian Network, as shown in Figure 19. As for the earthquake case, a distinction is made between deterministic/fixed variables and instantiable variables.

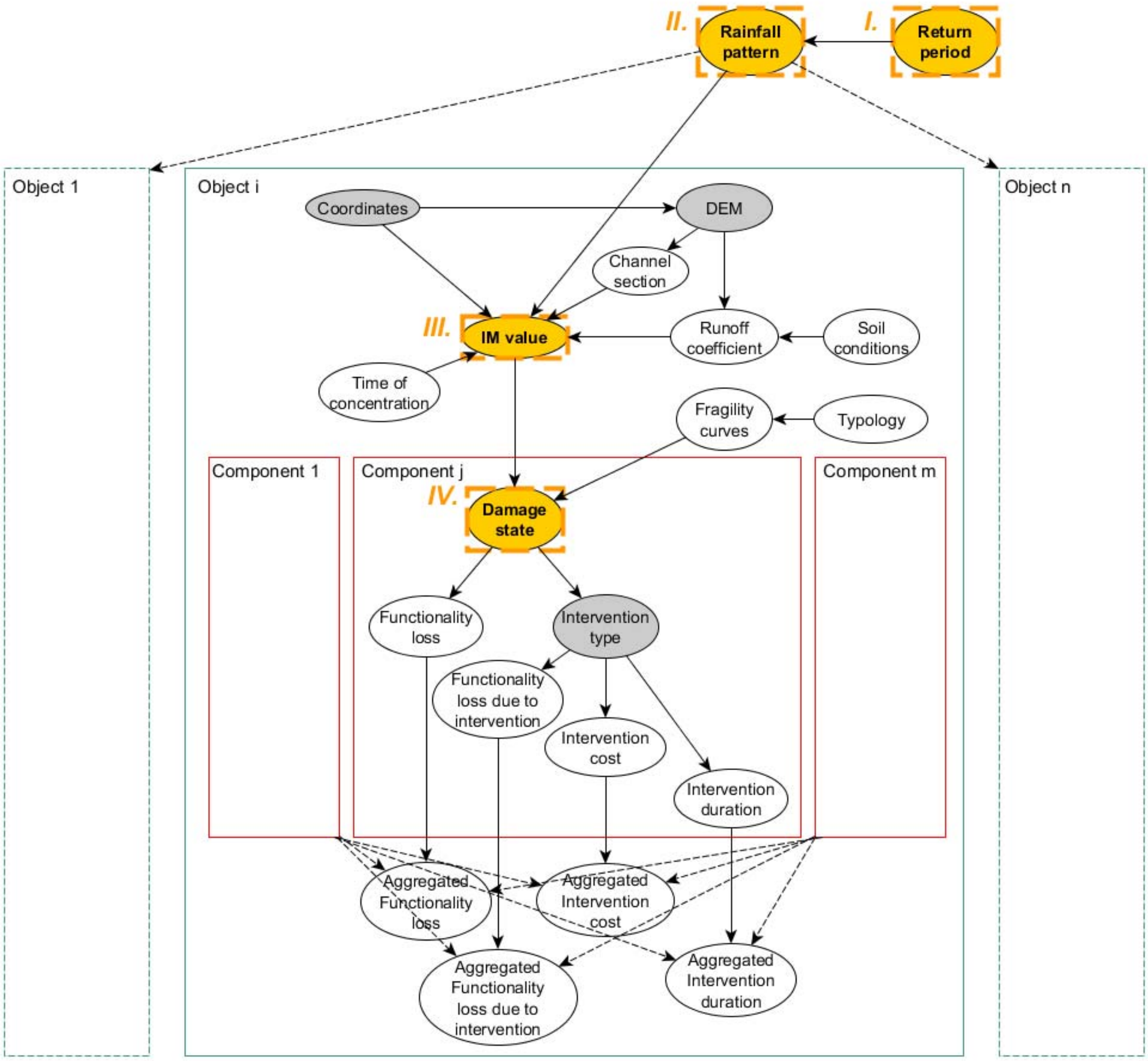

Figure 19: Bayesian Network structure for fluvial flood risk. The grey nodes represent the variables that can be assumed as deterministic and/or directly imposed by the state of the environment. The nodes within the dashed orange frame represent the variables that may be instantiated by the end-user (i.e. instantiation levels).

5.4 Corresponding decision tree for the IDST

The Bayesian Network in Figure 19 allows for the identification of four instantiation levels, which can be describedas follows:

- **Level I:** the return period is instantiated (i.e. selection of a given return period of interest), which means that the rest of the analysis will generate risk outputs for the same return period.
- **Level II:** the rainfall pattern is instantiated (i.e. selection of a single rainfall scenario with a given pattern of duration and intensity), which means that the rest of the analysis will be performed for the same single event.
- **Level III:** the fluvial flood parameters at the sites of interest are instantiated (i.e. direct use of fluvial flood maps as input), which means that the rest of the analysis will be performed for the same level of hazard.

- **Level IV:** the component damage states of all CI elements are instantiated (i.e. definition of the physical state of the network elements), which means that the rest of analysis will focus on the functional consequences of a given physical disruption of the CI system.

Based on this rationale, a decision tree can be defined in order to guide the IDST user on which variables to consider for each chosen level of instantiation (see Figure 20).

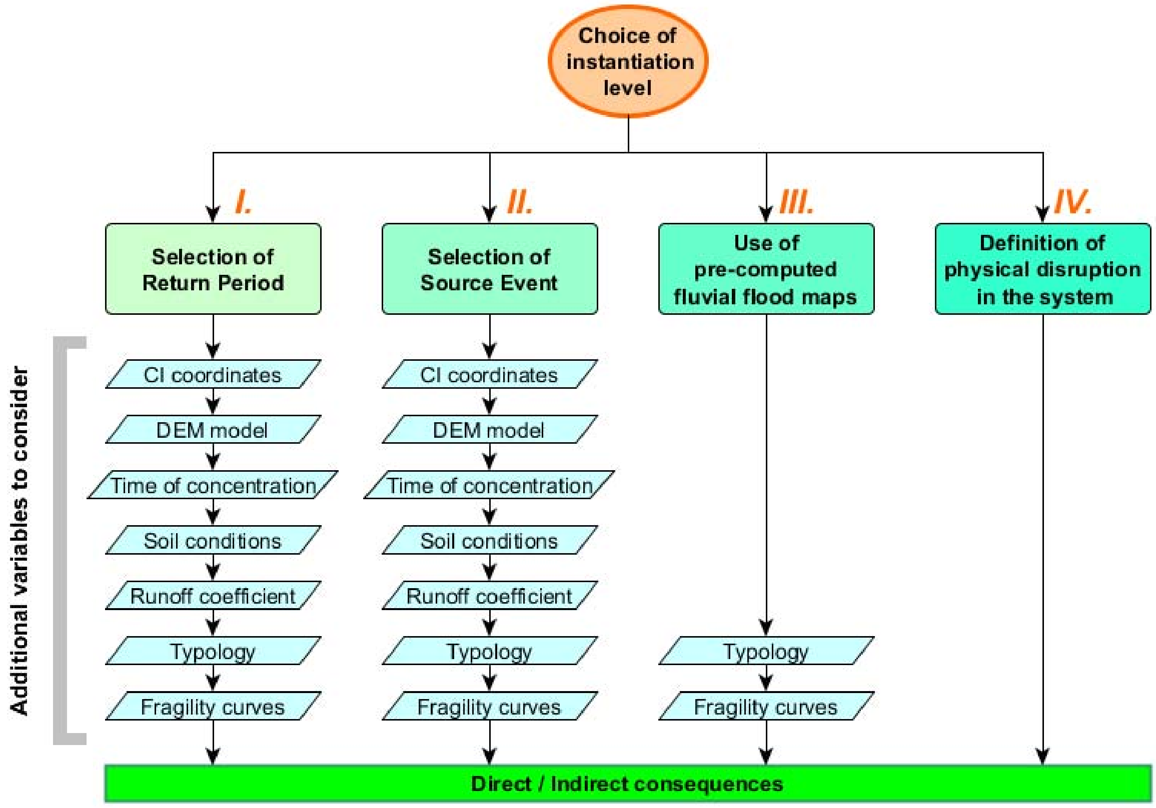

Figure 20: Decision tree for the fluvial flood risk analysis within the IDST.

5.5 Recommendations for the IDST structure and models

The analysis levels defined in Figure 20 are associated with different levels of complexity and computational load: for instance, the assessment of all probabilities deriving from levels *I* and *II* does not seem feasible within the IDST, due to the large number of variable samplings and model evaluations that would be required. However, the execution of levels *III* and *IV* is reasonable within the IDST, as long as the tasks and models detailed in Table 6 can be implemented.

Table 6: Models and data sets that are required in the IDST for each considered analysis level

Analysis level		Models and data
Level III	**Input data**	- GIS file of fluvial flood parameters at the locations of the CI elements - typology of the CI elements and corresponding structural components (i.e. attribute table in the GIS file) - catalogue of fragility functions

	Computations / Operations	- for each component, choice of a set of fragility functions given the typology (i.e. correspondence table between typologies and fragility functions) - computation of the component damage probabilities with the fragility model and the IM_local value - random sampling of the component damage states (i.e. use of a standard uniform variable to sample a given damage state out of the damage probabilities)
Level IV	**Input data**	- component damage states for all CI elements (i.e. outcome of level III) - correspondence table between component damage states and functionality losses (with or without uncertainties on the values) - correspondence table between component damage states and intervention types - correspondence table between intervention types and cost/duration (with or without uncertainties on the values) - correspondence table between intervention types and functionality losses during intervention (with or without uncertainties on the values)
	Computations / Operations	- determination of functionality loss based on component damage state (use of correspondence table + sampling on the uncertainties if available) - determination of intervention type based on component damage state (use of correspondence table) - determination of intervention cost and duration based on intervention type (use of correspondence table + sampling on the uncertainties if available) - determination of functionality loss during intervention based on intervention type (use of correspondence table + sampling on the uncertainties if available) - aggregation of losses/costs/repairs from the component-level to the CI element-level

6.0 SCOUR

This section details how the various variables and models have to be formalized in order to perform the scour risk analysis within the IDST.

6.1 Specification of the event tree

The following sub-sections specify the contents of the scour event tree, according to the structure proposed by the INFRARISK methodology (i.e. distinction between source, hazard, infrastructure and network events).

6.1.1 Source event

The main variables that are involved in the estimation of the source event are the following (see Figure 21):

- *Fluvial flood parameters (x,y):* flow discharge and water depth at the channel section located under the bridge of interest. Flood parameter values are computed for all the geographical locations that correspond to the coordinates of the CI elements (i.e. bridges, in the case of scour).

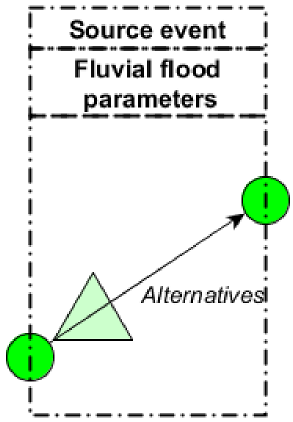

Figure 21: Source Event-tree structure for scour.

Based on the previously conducted fluvial flood analysis, the flood properties are already defined for each channel section. Therefore the source event is specific to each bridge object that may be susceptible to scour.

6.1.2 Hazard event

The hazard event-tree includes the three types of scour that may occur, namely general scour, contraction scour and local scour.

The main variables that are involved in the estimation of the hazard event are the following (see Figure 22):

- *Geographical coordinates of the CI element:* longitude and latitude representing the location of the object of interest (i.e. centroid of the bridge object).

- *Digital Elevation Model (DEM):* this model enables to evaluate the channel slope grade and the river section width, upstream and downstream (i.e. parameters required for the estimation of contraction scour).
- *Bed material properties:* parameters such as streambed material size or Manning's roughness coefficient.
- *Bed condition*: e.g., Clear Water or Live Bed conditions.
- *General scour*: excavated depth due to the channel itself, regardless of the existence of the substructure.
- *Contraction scour:* excavated depth due to narrowing generated by the structure.
- *Component type:* specification of the substructure of interest, namely pier or abutment.
- *Component properties:* if the component is a pier, the properties include shape of pier nose, pier width, and angle of the pier with respect to flow direction. If the component is an abutment, the properties the length and cross section of the embankment.
- *Local scour:* excavated depth due to turbulence created around piers and abutments.

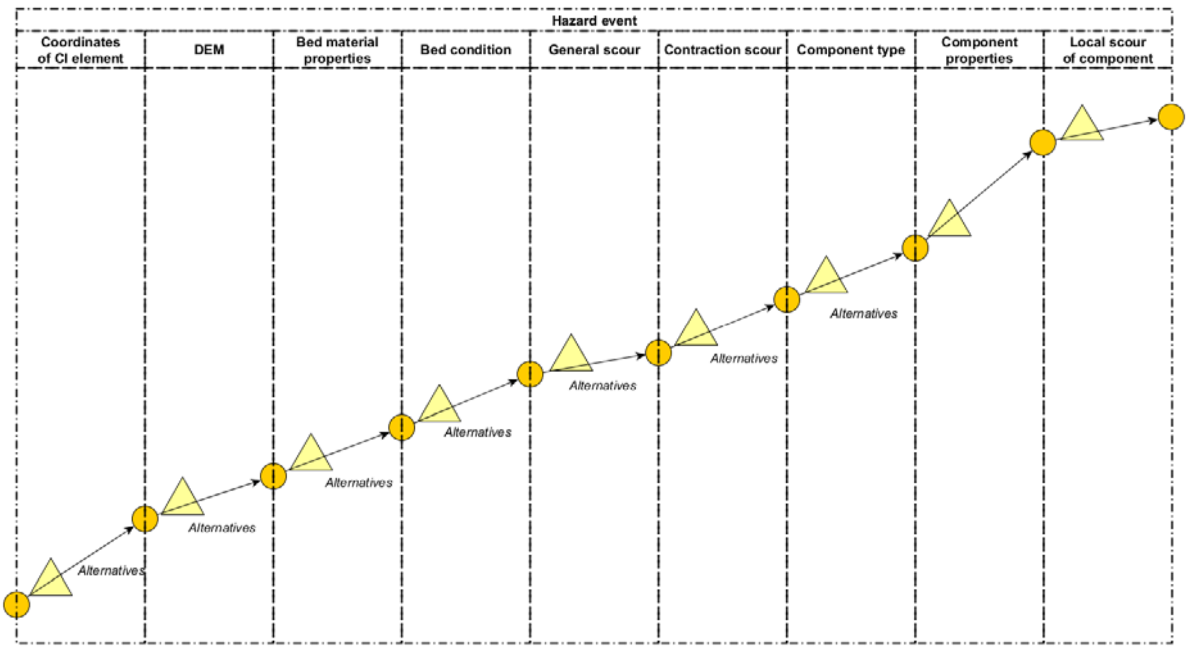

Figure 22: Hazard Event-tree structure for scour.

6.1.3 Infrastructure event

The Infrastructure Event-tree for scour is the same as the one for earthquakes (see Figure 8). It is assumed that only bridge objects are exposed to scour, while the components of interest are piers and abutments only.

In the case of scour, the term "damage state" may not be the most appropriate, in the sense that the effects of scour may include:

- actual structural damage, such as rotation/translation of the piers and the deck, until ultimately reaching collapse;
- alteration of the stiffness of the bridge piers as well as the boundary conditions (i.e. foundations system). In this case, scour damage may be referred to as “Updated capacity” or “Residual capacity”, due to the alteration of the lateral resistance of the piers.

6.1.4 Network event

The approach is similar to the event tree described in Section 3.1.4, Figure 9.

6.2 Uncertainty types

The different variables and their corresponding uncertainty sources are summarized in Table 7: this specification exercise is helpful for the construction and the interpretation of the Bayesian Belief Network in the next sub-section. As for the landslide risk analysis, it appears that the actual estimation of the scour value is a deterministic process, while the variability in the scour prediction is introduced by the epistemic uncertainties that are related to the input parameters, such as bed material properties.

Table 7: Summary of the main variables and their uncertainties used in the scour risk analysis

Event variables	Uncertainty type	Nature
Source event		
Fluvial flood parameters	Parameter	Continuous
Hazard event		
CI coordinates	*Deterministic*	
Digital Elevation Model	*Deterministic*	
Bed material properties	Parameter	Continuous
Bed condition	Parameter	Discrete
General scour	*Deterministic*	
Contraction scour	*Deterministic*	
Component	*Deterministic*	
Component properties	Parameters	Continuous
Local scour	*Deterministic*	
Infrastructure event		
Typology	Model	Discrete
Component	*Deterministic*	
Fragility curve	Model	Discrete
Damage state	Aleatory	Discrete
Network event		
Functionality loss	Aleatory	Continuous
Intervention type	*Deterministic*	
Cost/duration of intervention	Aleatory	Continuous
Functionality loss during intervention	Aleatory	Continuous

6.3 Corresponding Bayesian network

The event tree detailed above is translated into a Bayesian Network, as shown in Figure 23. As for the earthquake case, a distinction is made between deterministic/fixed variables and instantiable variables.

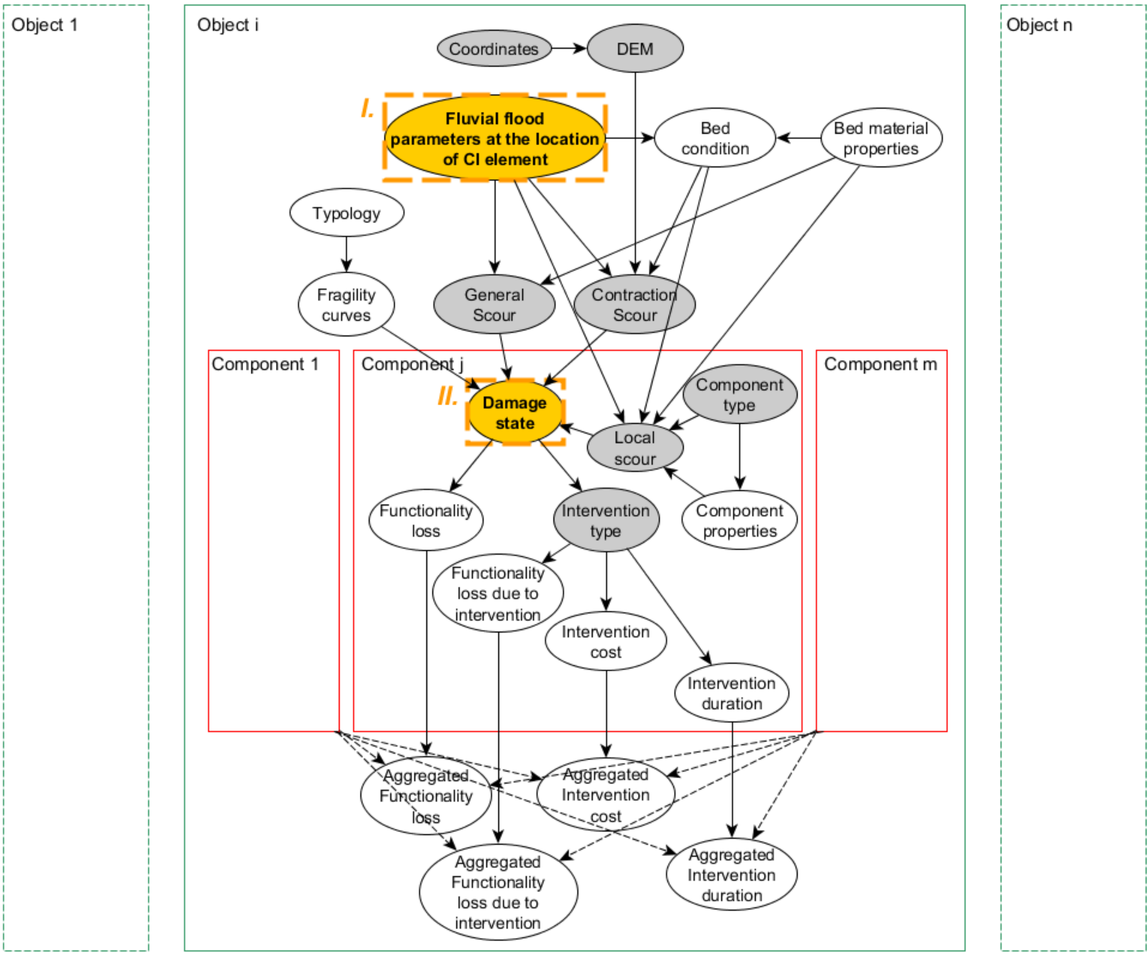

Figure 23: Bayesian Network structure for scour risk. The grey nodes represent the variables that can be assumed as deterministic and/or directly imposed by the state of the environment. The nodes within the dashed orange frame represent the variables that may be instantiated by the end-user (i.e. instantiation levels).

6.4 Corresponding decision tree for the IDST

The Bayesian Network in Figure 23 allows the identification of two instantiation levels, which can be described as follows:

- **Level I:** the fluvial flood parameters at the sites of interest are instantiated (i.e. direct use of fluvial flood maps as input), which means that the rest of the analysis will be performed for the same level of hazard.

- **Level II:** the component damage states of all CI elements are instantiated (i.e. definition of the physical state of the network elements), which means that the rest of analysis will focus on the functional consequences of a given physical disruption of the CI system.

Based on this rationale, a decision tree can be defined in order to guide the IDST user on which variables to consider for each chosen level of instantiation (see Figure 24).

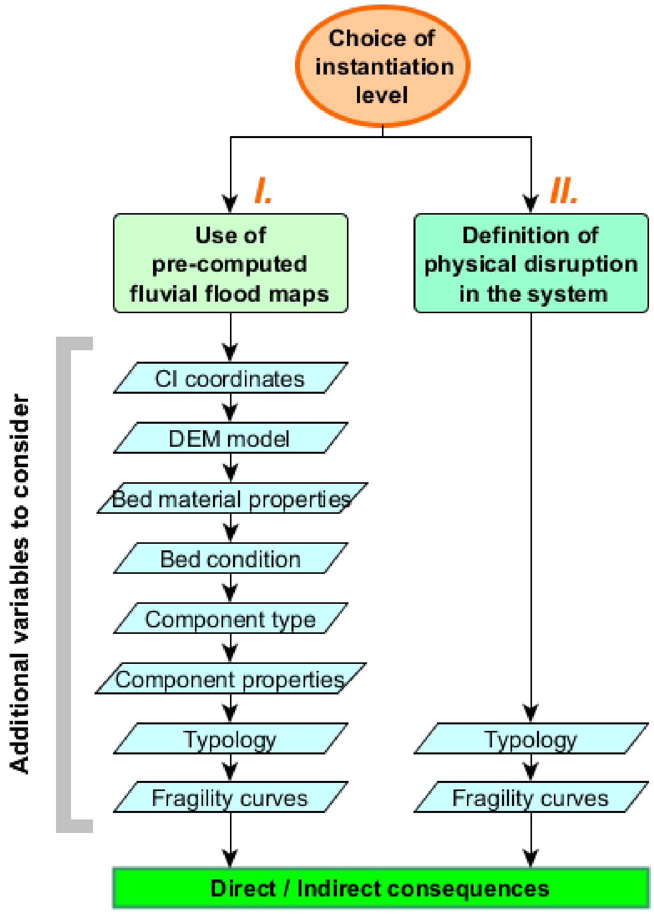

Figure 24: Decision tree for the scour risk analysis within the IDST.

6.5 Recommendations for the IDST structure and models

The analysis levels defined in Figure 24 are associated with different levels of complexity and computational load: in the present case, both levels *I* and *II* seem feasible within the IDST, since the scour hazard can be quantified locally thanks to the use of a map of fluvial flood parameters. The tasks and models that need to be implemented are detailed in Table 8.

Table 8: Models and data sets that are required in the IDST for each considered analysis level

Analysis level	Models and data	
Level I	**Input data**	- GIS file of fluvial flood parameters at the sites of interest - GIS file of CI elements - GIS file of Digital Elevation Model - Bed material properties (i.e. attribute table in the GIS file) - typology of the CI elements and corresponding structural components (i.e. attribute table in the GIS file) - properties of the piers and abutments (e.g. size, shape) - catalogue of fragility functions
	Computations / Operations	- evaluation of the streambed conditions (through deterministic equations or correspondence table) - evaluation of general scour (through deterministic scour equation) - evaluation of contraction scour (through deterministic scour equation) - evaluation of local scour (through deterministic scour equation) for each component (e.g. pier, abutment) - aggregation of total scour (addition of all scour types) - for each component, choice of a set of fragility functions given the typology (i.e. correspondence table between typologies and fragility functions) - computation of the component damage probabilities with the fragility model and the IM_local value - random sampling of the component damage states (i.e. use of a standard uniform variable to sample a given damage state out of the damage probabilities)
Level II	**Input data**	- component damage states for all CI elements (i.e. outcome of level I) - correspondence table between component damage states and functionality losses (with or without uncertainties on the values) - correspondence table between component damage states and intervention types - correspondence table between intervention types and cost/duration (with or without uncertainties on the values) - correspondence table between intervention types and functionality losses during intervention (with or without uncertainties on the values)
	Computations / Operations	- determination of functionality loss based on component damage state (use of correspondence table + sampling on the

	uncertainties if available) - determination of intervention type based on component damage state (use of correspondence table) - determination of intervention cost and duration based on intervention type (use of correspondence table + sampling on the uncertainties if available) - determination of functionality loss during intervention based on intervention type (use of correspondence table + sampling on the uncertainties if available) - aggregation of losses/costs/repairs from the component-level to the CI element-level

7.0 COASTAL FLOODING

This section details how the various variables and models have to be formalized in order to perform the coastal flood risk analysis within the IDST.

7.1 Specification of the event tree

The following sub-sections specify the contents of the coastal flooding event tree, according to the structure proposed by the INFRARISK methodology (i.e. distinction between source, hazard, infrastructure and network events).

7.1.1 Source event

The main variables that are involved in the estimation of the source event are the following (see Figure 25):

- *Return period of interest:* the selected return period of the wind pattern.
- *Wind pattern:* duration and intensity of wind speed.
- *Tide conditions.*

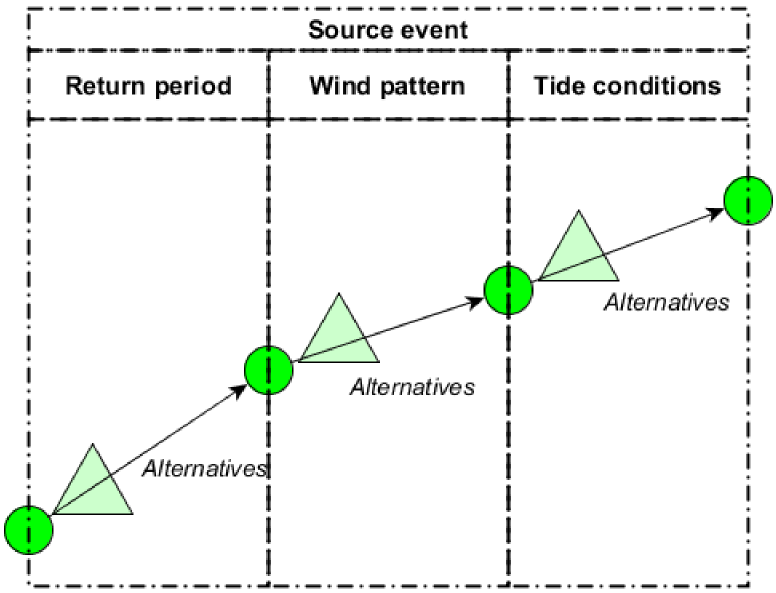

Figure 25: Source Event-tree structure for coastal flooding.

7.1.2 Hazard event

The main variables that are involved in the estimation of the hazard event are the following (see Figure 26):

- *Geographical coordinates of the CI element:* longitude and latitude representing the location of the object of interest. A proxy may have to be used, depending on the type of CI element considered (e.g. bridge, tunnel, road segment, slope), which could be described as a point, a line or a polygon (area).

- *Digital Elevation Model (DEM):* this model is required in order to obtain backshore topography to define hazard zones, obtain near shore bathymetry to define beach profiles, and define the geometry to evaluate hydrodynamic conditions.
- *Fetch length:* the length of water that is actually exposed to the wind.
- *IMs of interest*: either wind setup, wave height or wave period.
- *IM value (x,y)*: the actual hazard loading that is estimated at the site of interest. IM values are computed for all the geographical locations that correspond to the coordinates of the CI elements.

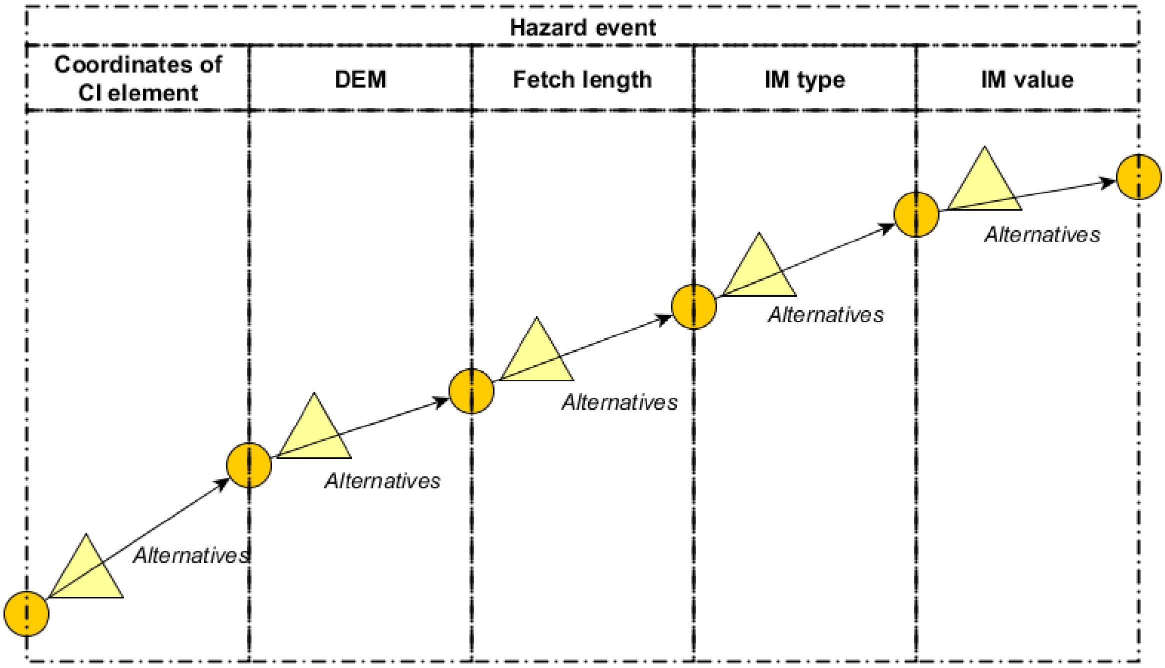

Figure 26: Hazard Event-tree structure for coastal flooding.

7.1.3 Infrastructure event

The Infrastructure Event-tree for coastal flooding is the same as the one for earthquakes (see Figure 8).

7.1.4 Network event

The approach is similar to the event tree described in Section 3.1.4, please refer to Figure 9.

7.2 Uncertainty types

The different variables and their corresponding uncertainty sources are summarized in Table 9: this specification exercise is helpful for the construction and the interpretation of the Bayesian Belief Network in the next sub-section.

Table 9: Summary of the main variables and their uncertainties used in the costal flood risk analysis

Event variables	Uncertainty type	Nature
Source event		
Return period of wind	Parameter	Continuous
Wind pattern	Parameter / Aleatory	Continuous
Tide conditions	Parameter / Aleatory	Continuous
Hazard event		
CI coordinates	*Deterministic*	
Digital Elevation Model	*Deterministic*	
Fetch length	Parameter	Continuous
IM type	Model	Discrete
IM value	Parameter / Aleatory	Continuous
Infrastructure event		
Typology	Model	Discrete
Component	*Deterministic*	
Fragility curve	Model	Discrete
Damage state	Aleatory	Discrete
Network event		
Functionality loss	Aleatory	Continuous
Intervention type	*Deterministic*	
Cost/duration of intervention	Aleatory	Continuous
Functionality loss during intervention	Aleatory	Continuous

7.3 Corresponding Bayesian network

The event tree detailed above is translated into a Bayesian Network, as shown in Figure 27. As for the earthquake case, a distinction is made between deterministic/fixed variables and instantiable variables.

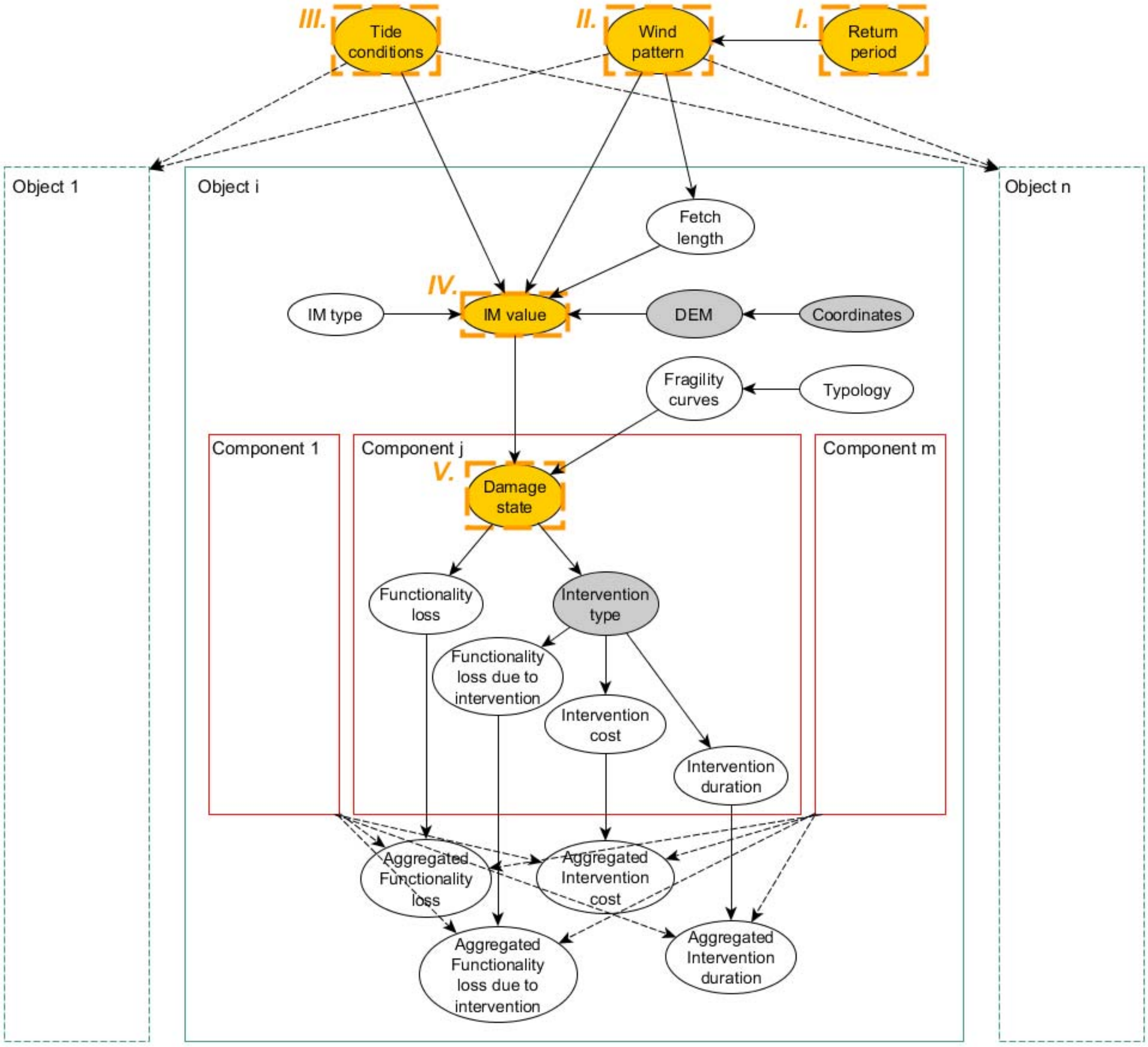

Figure 27: Bayesian Network structure for coastal flooding risk. The grey nodes represent the variables that can be assumed as deterministic and/or directly imposed by the state of the environment. The nodes within the dashed orange frame represent the variables that may be instantiated by the end-user (i.e. instantiation levels).

7.4 Corresponding decision tree for the IDST

The Bayesian Network in Figure 27 allows the identification of five instantiation levels, which can be described as follows:

- **Level I:** the wind return period is instantiated (i.e. selection of a given return period of interest), which means that the rest of the analysis will generate risk outputs for the same wind return period.
- **Level II:** the wind pattern is instantiated (i.e. selection of a single wind scenario with a given pattern of duration and intensity), which means that the rest of the analysis will be performed for the same single wind event.
- **Level III:** the tide conditions are instantiated, which means that the rest of the analysis will be performed for the same single wind and tide event.

- **Level IV:** the flood parameters at the sites of interest are instantiated (i.e. direct use of coastal flood maps as input), which means that the rest of the analysis will be performed for the same level of hazard.
- **Level V:** the component damage states of all CI elements are instantiated (i.e. definition of the physical state of the network elements), which means that the rest of analysis will focus on the functional consequences of a given physical disruption of the CI system.

Based on this rationale, a decision tree can be defined in order to guide the IDST user on which variables to consider for each chosen level of instantiation (see Figure 28).

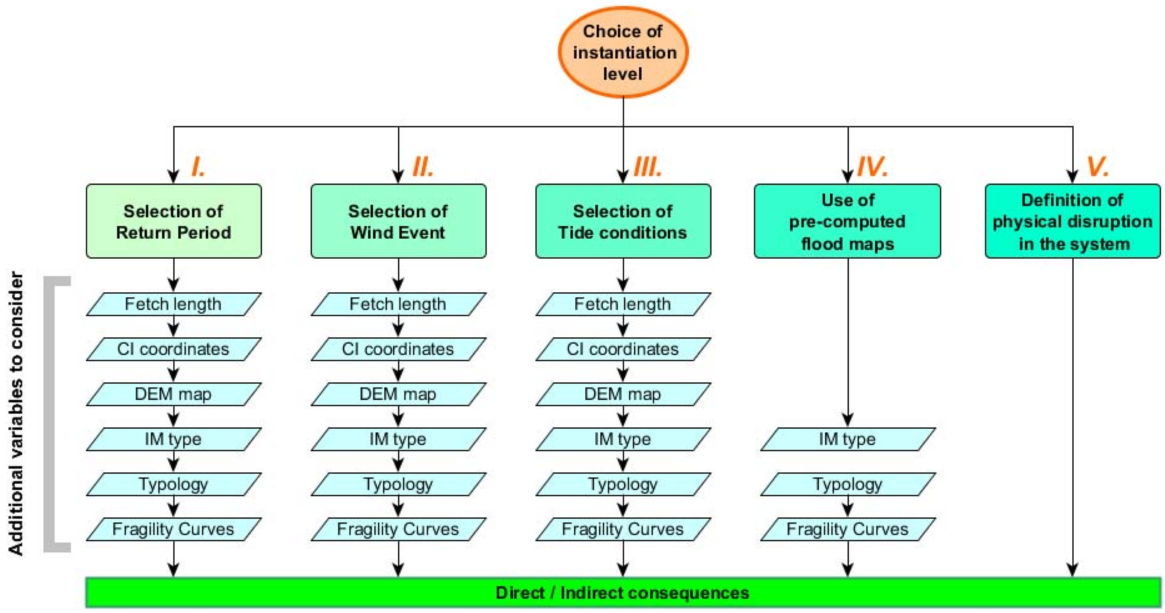

Figure 28: Decision tree for the scour risk analysis within the IDST.

7.5 Recommendations for the IDST structure and models

The analysis levels defined in Figure 28 are associated with different levels of complexity and computational load: for instance, the assessment of all probabilities deriving from levels *I* to *III* does not seem feasible within the IDST, due to the large number of variable samplings and model evaluations that would be required. However, the execution of levels *IV* and *V* is reasonable within the IDST, as long as the tasks and models detailed in Table 10 can be implemented.

Table 10: Models and data sets that are required in the IDST for each considered analysis level

Analysis level		Models and data
Level IV	**Input data**	- GIS file of coastal flood parameters at the locations of the CI elements - typology of the CI elements and corresponding structural components (i.e. attribute table in the GIS file) - catalogue of fragility functions
	Computations	- for each component, choice of a set of fragility functions given the typology (i.e. correspondence table between

	/ Operations	typologies and fragility functions) - computation of the component damage probabilities with the fragility model and the IM_local value - random sampling of the component damage states (i.e. use of a standard uniform variable to sample a given damage state out of the damage probabilities)
Level V	**Input data**	- component damage states for all CI elements (i.e. outcome of level IV) - correspondence table between component damage states and functionality losses (with or without uncertainties on the values) - correspondence table between component damage states and intervention types - correspondence table between intervention types and cost/duration (with or without uncertainties on the values) - correspondence table between intervention types and functionality losses during intervention (with or without uncertainties on the values)
	Computations / Operations	- determination of functionality loss based on component damage state (use of correspondence table + sampling on the uncertainties if available) - determination of intervention type based on component damage state (use of correspondence table) - determination of intervention cost and duration based on intervention type (use of correspondence table + sampling on the uncertainties if available) - determination of functionality loss during intervention based on intervention type (use of correspondence table + sampling on the uncertainties if available) - aggregation of losses/costs/repairs from the component-level to the CI element-level

8.0 CONCLUSION

The present report has presented various ways of organizing and visualizing the different factors and models that are involved in the risk analysis, for each of the hazard types considered in INFRARISK. From the point of view of uncertainties, the different variables have been classified and organized within event trees, which represent all the steps of the risk analysis (i.e. source, hazard, infrastructure and network events). Event trees can also be represented as Bayesian Belief Networks, so that the logical relations between variables are emphasized. Whether the variables are considered as deterministic or probabilistic has important implications on the Bayesian network, in terms of the number of nodes required to describe the problem and resultant computational effort required.

Therefore different instantiation levels have been defined in each Bayesian network, so that the resulting risk analysis is more or less probabilistic or deterministic. These 'analysis levels' are essential to understand which type of analysis is feasible or not within the IDST. For each hazard type, the following analysis levels may be implemented into the IDST:

- **Earthquake risk:** computation of a single source-event scenario, from an earthquake event up to functionality losses.
- **Landslide risk:** use of deterministic skakemaps and soil saturation ratio to estimate landslide hazard and to compute the resulting functionality losses.
- **Flood risk:** direct use of pre-computed fluvial flood maps in order to compute functionality losses.
- **Scour risk:** use of deterministic fluvial flood maps to estimate scour hazard and to compute the resulting functionality losses.
- **Coastal flood risk:** direct use of pre-computed coastal flood maps in order to compute functionality losses.

For each hazard type, the different data sets and models that are needed in the IDST are also detailed: they are essentially comprised of GIS shapefiles, look-up tables, deterministic equations and a few sampling algorithms (i.e. for aleatory uncertainty). In the case that epistemic uncertainties need to be evaluated, additional computational loops could be added to the IDST, so that the various parameters and models can be sampled.

Finally, it should be noted that hazard computations for fluvial and coastal floods are not straightforward and their implementation within the IDST is therefore a major challenge for users. Given this difficulty it is recommended therefore that at present the risk analysis performed using the platform should be limited to a damage analysis, based on deterministic pre-computed hazard maps. It should still be possible to input different hazard maps, in order to obtain some variability from the hazard loading parameters. Whatever the hazard type considered, the algorithms related to the Infrastructure and Network Events remain the same, so that they have only to be implemented once into the IDST.

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Appendix A SOIL CLASSIFICATION FOR SEISMIC HAZARD ASSESSMENT

A.1 Eurocode 8 (EC8) soil classes

Table 11: Description of EC8 soil classes (Eurocode, 1998), based on $V_{s,30}$ (mean shear wave velocity over the first 30m), N_{SPT} (standard penetration test) and c_u (undrained cohesion).

Ground type and description	$V_{s,30}$ [m/s]	N_{SPT}	c_u [kPa]
A: Rock or other rock-like geological formation, including at most 5 m of weaker material at the surface.	>800	-	-
B: Deposits of very dense sand, gravel, or very stiff clay, at least several tens of meters in thickness, characterized by a gradual increase of mechanical properties with depth.	360-800	>50	>250
C: Deep deposits of dense or medium dense sand, gravel or stiff clay with thickness from several tens to many hundreds of meters.	180-360	15-50	70-250
D: Deposits of loose-to-medium cohesionless soil (with or without some soft cohesive layers), or of predominantly soft-to-firm cohesive soil.	<180	<15	<70
E: A soil profile consisting of a surface alluvium layer with *v*s values of type C or D and thickness varying between about 5 m and 20 m, underlain by stiffer material with *v*s > 800 m/s.			
S_1: Deposits consisting, or containing a layer at least 10 m thick, of soft clays/silts with a high plasticity index (PI > 40) and high water content	<100	-	10-20
S_2: Deposits of liquefiable soils, of sensitive clays, or any other soil profile not included in types A – E or S_1			

A.2 The US National Earthquake Hazard Reduction Provisions (NEHRP) soil classes

Table 12: Description of NEHRP soil classes (BSSC, 1995), based on $V_{s,30}$ (mean shear wave velocity over the first 30m).

Ground type and description	$V_{s,30}$ [m/s]
A: Hard rock.	>800
B: Rock.	360-800
C: Very dense soil and soft rock.	180-360
D: Stiff soil profile.	<180
E: Soft soil profile.	

Appendix B BAYESIAN NETWORKS FOR SEISMIC RISK ANALYSIS

B.1 Level I: Selection of a Return Period

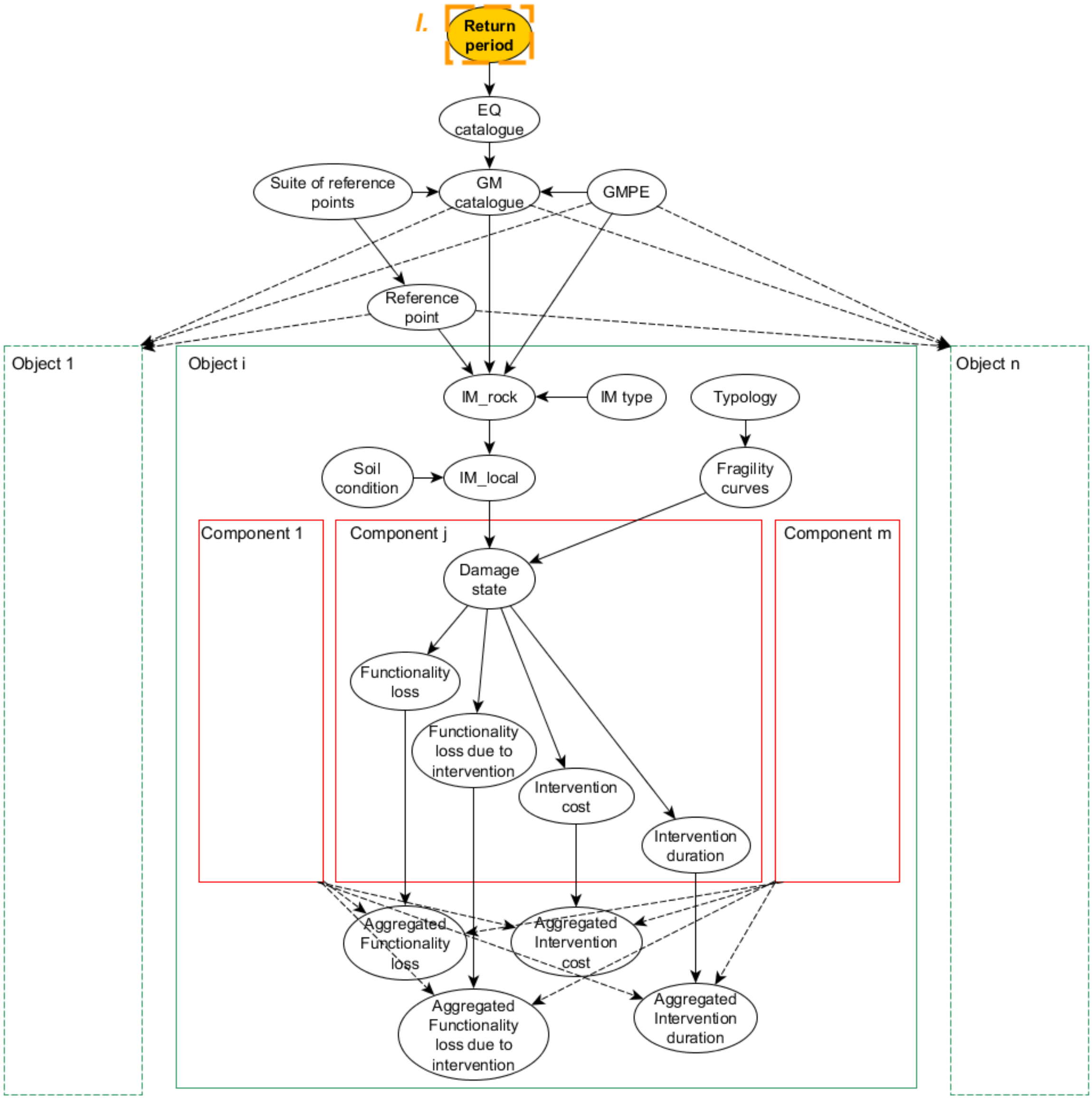

Figure 29: Bayesian Network structure for seismic risk for analysis level I. The node within the dashed orange frame represents the instantiated variable.

B.2 Level II: Selection of a Reference Point

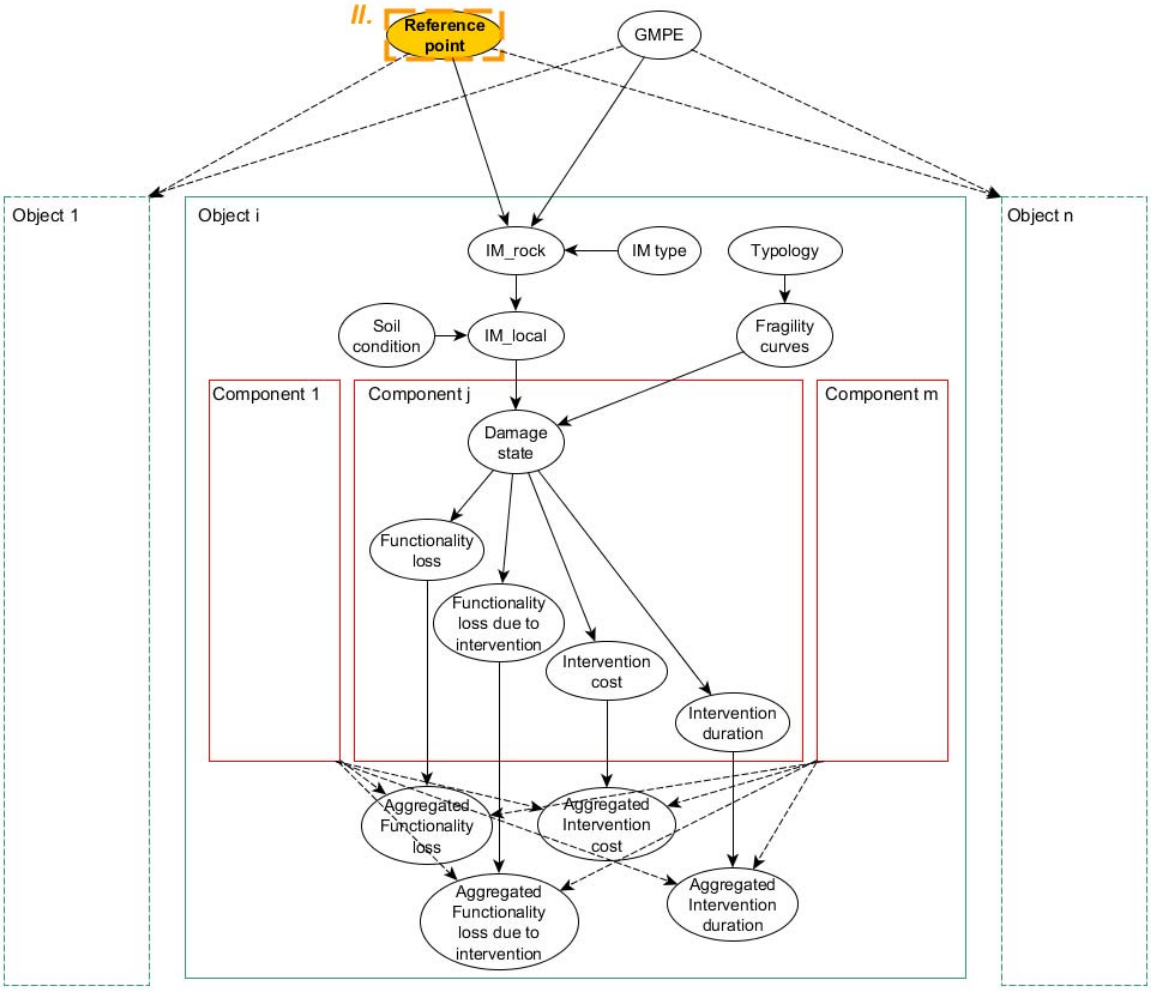

Figure 30: Bayesian Network structure for seismic risk for analysis level II. The node within the dashed orange frame represents the instantiated variable.

B.3 Level III: Use of a deterministic shake-map

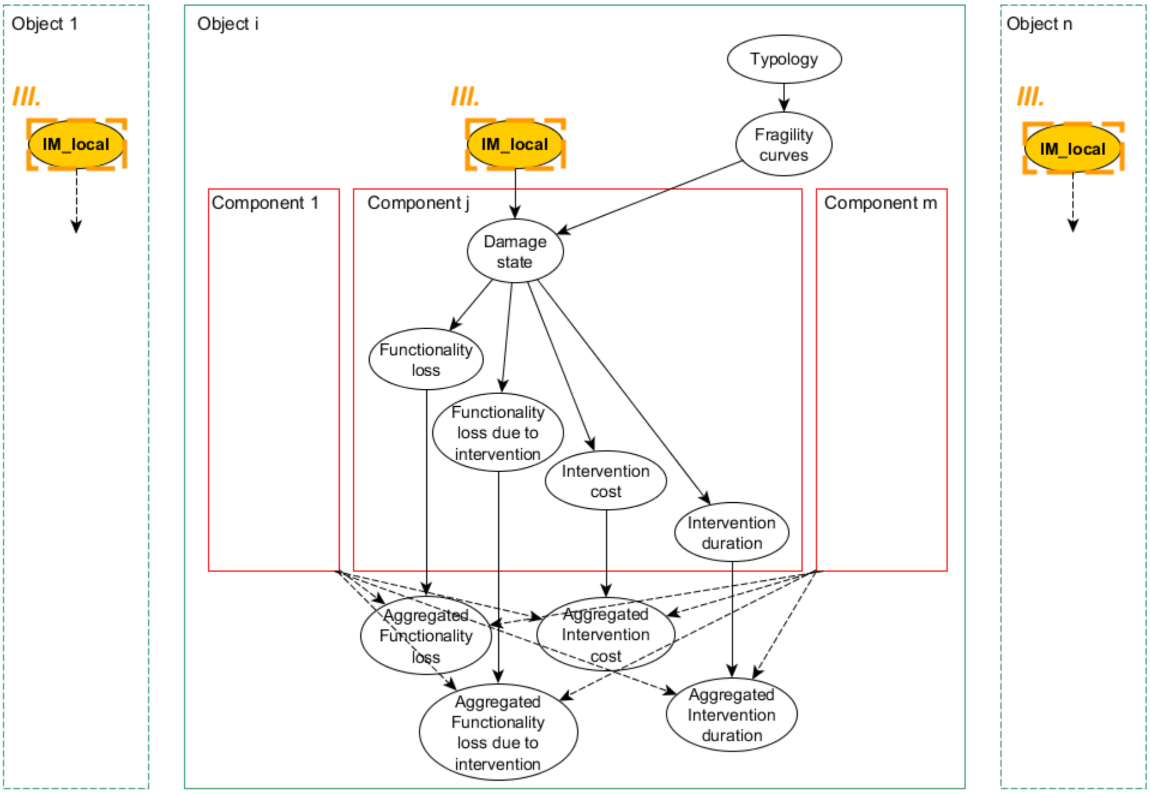

Figure 31: Bayesian Network structure for seismic risk for analysis level III. The node within the dashed orange frame represents the instantiated variable.

B.4 Level IV: Use of a deterministic damage map

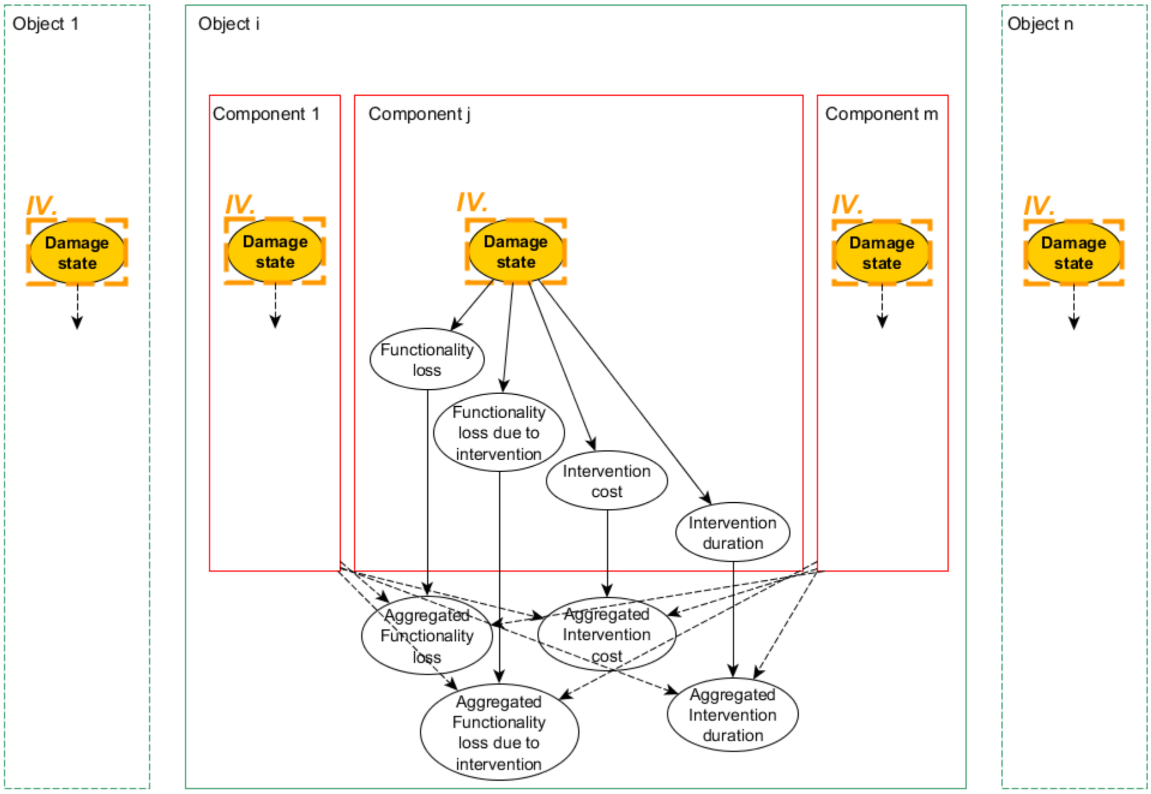

Figure 32: Bayesian Network structure for seismic risk for analysis level IV. The node within the dashed orange frame represents the instantiated variable.