Chapter 7
Vulnerability Modelling

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7.1 Introduction

Vulnerability, understood as the conditions determined by physical, social, economic and environmental factors or processes that increase the potential for an individual, a community, assets or systems to be negatively affected by hazards (adapted from UNDRR, 2017), is a key component when assessing tsunami risk. Vulnerability can be affected by human interventions. Hence, the study of vulnerability is essential to

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support decision-making (e.g., land use planning and emergency planning) for more effective risk management.

A vulnerability assessment in a probabilistic analysis typically comprises the evaluation of potential losses that the natural process may cause to exposed assets (physical vulnerability) and people and communities (social vulnerability) in terms of monetary losses and casualties, respectively. Vulnerability is most commonly represented through a vulnerability function that expresses the likelihood of achieving a value of a loss parameter for increasing values of a hazard intensity measure. Vulnerability functions can be derived "directly" by fitting a statistical model to post-event loss data (empirical) or through the elicitation of expert opinion (heuristic). Vulnerability functions can be derived "indirectly" from the combination of fragility functions and a consequence model, also called damage-to-loss model (Rossetto and Ioannou 2018).

A fragility function expresses the likelihood of damage that will be sustained by a physical asset under increasing tsunami intensity values, and sets of fragility functions are commonly produced, with each individual fragility function representing the likelihood of exceedance of a specific damage state (DS), such as "collapse" or "heavy damage", conditioned on the expected intensity measure (IM), as given in Eq. (7.1) and illustrated in Fig. 7.1a:

$$\mathrm{P}(DS \geq ds_{\mathrm{i}} | IM) \tag{7.1}$$

To make the fragility analysis representative of the different structural responses to tsunami loading, buildings are typically classified according to structural properties and the fragility analysis is carried out for each class separately (Charvet et al. 2017). For example, recent research works have developed fragility curves for tsunami that consider structural type, material of the structure, construction year, and height, among other parameters (Nanayakkara and Dias, 2016; Macabuag et al. 2016a; Suppasri et al. 2014; Petrone et al. 2017; Valencia et al. 2011).

Vulnerability functions are defined as relationships providing the expected level of loss for a given IM, as expressed by Eq. (7.2):

$$P(L > l \,|\, IM) \tag{7.2}$$

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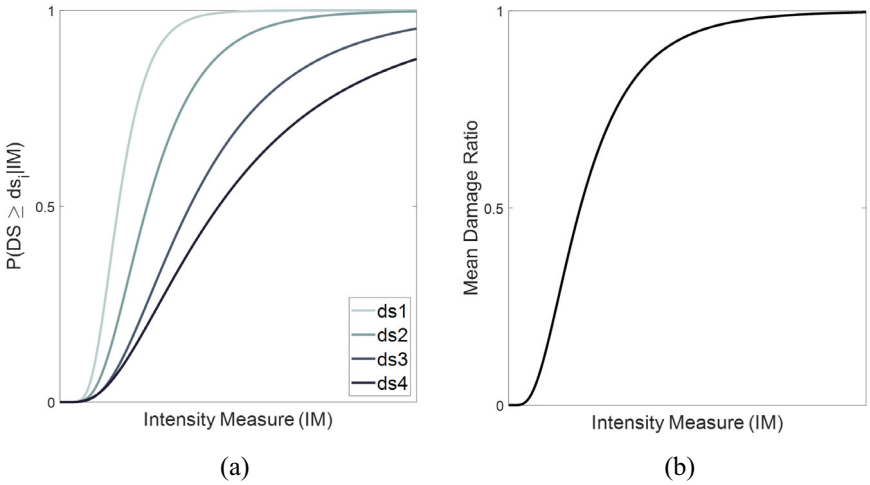

Fig. 7.1 Typical representation of **a** fragility functions and **b** vulnerability functions

where L is the loss parameter for a given asset (e.g., in terms of repair costs). Many vulnerability functions are given in terms of mean damage ratio (MDR) as a function of the IM - see Fig. 7.1b. MDR is defined as the expected value of the ratio of the cost of repair divided by the cost of replacement of the asset (repair-to-replacement cost ratio). Vulnerability functions can include the percentage of loss directly, where loss amount is used as the measure of impact when building the curve, e.g., when using insurance claims data.

Fragility functions can be transformed into "indirect" vulnerability functions using consequence models - see Fig. 7.2. For example, a typical tsunami consequence model used in the physical vulnerability assessment of buildings comprises a set of damage ratios (or loss ratios) for given damage states and takes values between 0.0 and 1.0 for no damage to collapse, respectively. In the case of human vulnerability, casualty rates are instead the most common form of consequence function (Rossetto et al. 2014). These express the proportion of occupants in a building that are likely to be injured/die conditioned on the building damage state. In both cases of consequence model, the damage ratios or casualty rates may have deterministic values for each damage state or present a mean value with standard deviation. Indirect vulnerability evaluation through use of fragility functions curves and consequence models is based on the fundamental assumption that the main cause of loss is due to asset damage (Rossetto et al. 2014). This assumption derives from earthquake risk assessment, and although it is realistic for the case of tsunami physical vulnerability evaluation, it does not hold true for tsunami human vulnerability evaluation, as the tsunami inundation can directly cause human fatalities.

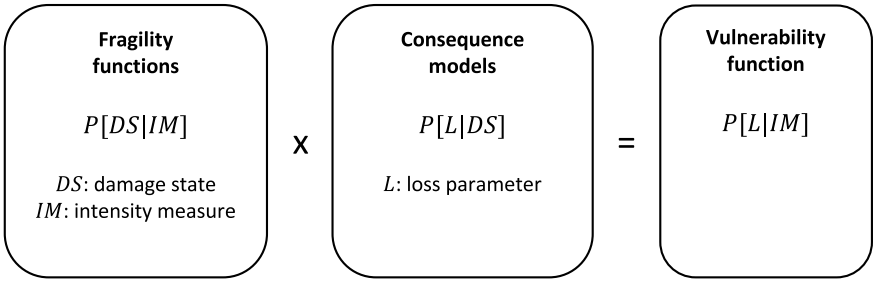

Fig. 7.2 Pseudo-formula for an "indirect" vulnerability function

Compared to earthquake vulnerability modelling, there are relatively few fragility functions for buildings and infrastructure under tsunami loading, and most of these are empirical in nature. Empirical fragility functions are developed by fitting a statistical model to observational data from real events. Charvet et al. (2017) present a review of available empirical fragility models and shows that these derive from observations made after a small number of recent tsunami events, given the rarity of this hazard. Empirical tsunami fragility functions are specific to the event and the location affected by the tsunami. Damage scales (e.g. MLIT, 2014, EEFIT, 2006, Fraser et al. 2013) are used to record levels of damage. These should then be used in the definition of each DS curve in the fragility function. It is also seen that most empirical fragility functions adopt inundation depth as an IM (e.g., Reese et al. 2011; Suppasri et al. 2011; Charvet et al. 2014a; De Risi et al. 2017a), since the inundation depth is measurable in the aftermath of a tsunami and can also be simulated numerically with relatively small errors. The values of the selected IMs are recorded through visual inspections after the event. For instance, if the inundation depth is the IM to use, then what is collected are the values of that measure (e.g., 1.5 m). However, it is often difficult to accurately determine the exact values of the IM. In the case of earthquake triggered tsunami, damage observations for buildings may reflect the cumulative action of both earthquake ground shaking and tsunami inundation, increasing the uncertainty.

Recently, advances in tsunami structural simulation approaches have led to the development of analytical fragility functions (e.g., De Risi et al. 2017b; Rossetto and Ioannou 2018). A review of existing analytical methods is provided by Rossetto et al. (2019). New analytical methods are based on the application of the tsunami load either in a dynamic regime according to tsunami inundation simulations or in a static load regime that mimics the effects of tsunami loads. While empirical fragility curves are typically obtained at community-scale for many buildings and assets, analytical fragility curves have been mostly developed at single-building level (e.g., Petrone et al. 2017; Alam et al. 2018; Karafagka et al. 2018). Only a few analytical studies have been developed at community level (e.g., Park et al. 2013; Aránguiz et al. 2018).

Approaches used for many years to understand physical vulnerability and model physical damages are now being applied to social vulnerability. When an approach is required encompassing several criteria, dimensions (e.g., social, physical, economic and environmental), and variables with different magnitudes and ranges of values, it may be necessary to apply an indicator-based approach (Aguirre-Ayerbe et al. 2018). There are some methods and operational tools available to facilitate the implementation of these approaches through the use of quantitative and qualitative indicators, e.g., the conceptual frameworks proposed by Aguirre-Ayerbe et al. (2018) and Strunz et al. (2011). The Papathoma Tsunami Vulnerability Assessment (PTVA) model (Papathoma et al. 2019) is one of the most widely used index-based methods for the assessment of physical vulnerability of buildings to tsunami. Index-based methods can feed into policies such as the Sendai Framework for Disaster Risk Reduction (SFDRR) 2015–2030 (UNISDR, 2015). There are emerging studies that aim to improve the way vulnerability is evaluated that are not necessarily constrained to physical vulnerability (Salmanidou et al. 2021; Himaz, 2022). Issues such as displacements and migration, pertaining to social conflicts, poverty, marginalisation and political vulnerabilities are areas that can significantly affect human and social vulnerability but tend to be avoided due to the challenging methods to quantify (Table 7.1).

7.2 Empirical Physical Vulnerability

7.2.1 Short Description

An empirical tsunami vulnerability function consists of a set of statistical models correlating some Explanatory Variables (EV) to some Response Variables (RV) based on observed tsunami events. A very comprehensive literature review of empirical models is provided by Charvet et al. (2017).

EVs are IMs and built environment characteristics. Examples of IMs are the inundation depth (h), tsunami velocity (v), moment flux (hv^2), moment of momentum flux (MMF), drag force (F), the quasi-steady tsunami force (FQS), and the debris impact. EVs describing the built environment include the building construction materials and typologies (e.g., Timber, Masonry, Reinforced Concrete, Moment resisting Frame, Shear Wall) and the coast type (e.g., Plain and Ria type).

For direct vulnerability models the RV is a measure of loss, such as loss ratios (cost of repair to replacement) for physical assets, or casualty rates. However, few direct empirical tsunami vulnerability functions exist. It is noted that the number of casualties (fatalities and injuries) depends on many variables, both physical and socio-economic ones, and is often expressed as a function of occupancy or of population (Marchand et al. 2009). Examples of empirical casualty models can be found in Berryman et al. (2005) and Reese et al. (2007). Most vulnerability functions are derived indirectly from fragility functions. Given this, the following text relates mainly to tsunami fragility functions.

Table 7.1 Summary table for tsunami vulnerability

What does the ingredient describe?	The assessment of the impact that tsunami may cause to exposed assets (physical vulnerability) and people and communities (social vulnerability)
Definitions of the ingredient	Tsunami vulnerability is understood as the conditions determined by physical, social, economic and environmental factors or processes that increase the potential for an individual, a community, assets or systems to be affected by tsunami
What is/are the metric(s) used for measuring/ evaluating the ingredient?	Tsunami vulnerability is commonly represented through a vulnerability function that expresses the likelihood of achieving a value of a loss parameter for increasing values of a hazard intensity measure. Many vulnerability functions are given in terms of mean damage ratio (MDR) as a function of the intensity measure (IM)
Possible uses/applications of the ingredient	The study of tsunami vulnerability is a key part in a tsunami risk assessment, which is essential to support decision-making for effective tsunami risk management
Possible multi-hazard dimensions/ applications?	Tsunami vulnerability models can be used to develop combined models that assess the impact of earthquake ground shaking and tsunami hazards simultaneously
Possible time-dependent/dynamic aspects	Tsunami vulnerability models can include accounting for the preceding earthquake damage due to near-field earthquake sources
List of the available methods to be described below	Empirical methods: a set of statistical models correlating some Explanatory Variables (EV) to some Response Variables (RV) based on observed tsunami events. Analytical methods: physical fragility functions are developed using a damage scale and transformed into vulnerability functions using consequence models. Indicator-based methods: vulnerability is evaluated qualitatively through indicators, which are operational representation of building exposure characteristics or the characteristics of the surroundings.

Fragility functions take a similar form to vulnerability functions but the RV used most typically is the DS, representing a damage condition experienced by the exposed physical asset to the tsunami. DS may vary from no damage to washed away. The descriptions of DS are not necessarily consistent among the reference publications, and the number of DS may vary from just 2 to more than 5. For instance, the Japanese Ministry of Land, Infrastructure, and Transportation (MLIT, 2014) adopts seven

damage states, namely no damage (DS1), minor damage (DS2), moderate damage (DS3), major damage (DS4), complete damage (DS5), collapse (DS6), and wash-away (DS7). All the available empirical methods are based on tsunami damage databases that do not account for potential initial damage induced by the ground shaking caused by the triggering earthquake. However, it is evident that an initial earthquake effect/damage level is often present for structures damaged by a subsequent tsunami, especially in the case of near-field events. Small levels of ground shaking can cause damage in the physical assets that is exacerbated by the subsequent tsunami, and high levels of ground shaking could directly collapse assets before the tsunami hits. Both types of induced seismic damage can lead to potential overestimations and more in general bias on the final tsunami fragility functions. It is important to stress that the information on non-damaged assets (i.e., DS1) is as important as the information on damaged assets (i.e., DS > 1); therefore, it cannot be neglected.

Fragility functions can be mono-dimensional (i.e., a simple curve generally resembling a Cumulative Distribution Function) or multidimensional (i.e., a surface function of more than one IM). Examples of both typologies of fragility function are shown in Fig. 7.3. More advanced models (i.e., the ones using multiple parameters or machine-learning-based ones) are more challenging to represent, and in general, they are provided with coded functions ready to use (e.g., De Risi et al. 2017c).

Statistical methods used for the development of empirical fragility models are the Ordinary Least Squares Method (OLS), (e.g., Peiris and Pomonis, 2005; Dias et al. 2009; Gokon et al. 2009; Koshimura et al. 2009; Suppasri et al. 2009, 2011, 2012a, 2012b, 2014; Koshimura and Kayaba, 2010; Murao and Nakazato 2010; Valencia et al. 2011; Amakuni and Terazono, 2011; Koshimura and Gokon, 2012; Mas et al. 2012; Nihei et al. 2012; Hayashi et al. 2013; Maruyama et al. 2013; Narita and Koshimura, 2015; Tanaka and Kondo, 2015) and the Generalised Linear Model (GLM), (e.g. Reese et al. 2011; Charvet et al. 2014a, 2014b; Macabuag et al. 2016a,

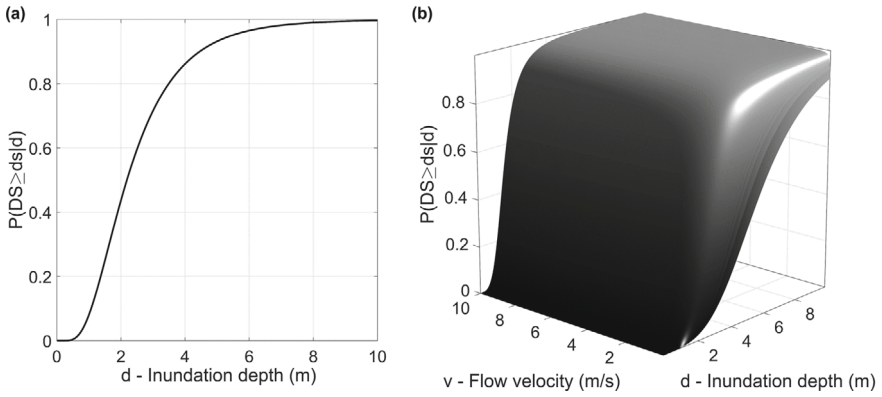

Fig. 7.3 Fragility of wooden structures: **a** monodimensional fragility function for collapse according to Suppasri:2013; and **b** multidimensional fragility for collapse/washed away (data from De Risi et al. (2017b))

2016b, 2018; Song et al. 2017; De Risi et al. 2017a, 2017b; Lahcene et al. 2021). More recently, Machine Learning (ML) algorithms have been used to develop such models (Mas et al. 2020; Rasheed et al. 2022).

OLS methods are the most traditional and used based on the probability-paper approach, where data for each damage class are binned for specific IM values and then fitted with a Normal or Log-Normal functional shape. These models are conventionally used to derive mono-dimensional models. Moreover, such models can be used when only a few data are available.

GLMs have recently become more popular because they allow for easier implementation of multivariate models and hence the use of multiple EVs at once. Specifically, GLM connects the damage probability with a linear predictor using simple formulations (e.g., probit, logit). Such a predictor is a simple linear combination of the explanatory variables since the coefficients of the linear combination are the object of the regression. However, GLMs need large databases to work correctly.

ML algorithms are used both for the automatic remote classification of damage and for the fitting of data. The simplest approach for the development of fragility models is the Artificial Neural Network (ANN), where the input layer consists of the EVs and the output layer provides the damage classification. The input layer and the damage classification are linked via a number of internal layers and nodes that may be the object of optimisation. Since such models do not need computational power as they are statistical tools, no cluster analyses or parallelisations are required. However, ML approaches may require more computational time with respect to OLS and GLMs as some model training is needed; however, this additional time is not comparable to the time needed, for example, for tsunami propagation and inundation analyses.

The abundance of potential methods and models requires the need for robust approaches for model diagnosis and selection. These may consist either in performing statistical tests (e.g., likelihood ratio test) or in looking at indicators, such as the Bayesian Information Criterion -BIC- (Schwarz, 1978), the Akaike Information Criterion -AIC- (Akaike, 1974), and the residual deviance. In general, the models presenting the smallest diagnostic indicator are the preferred ones. More sophisticated approaches also exist in the literature (Jalayer et al. 2022) consisting of simulation-based Bayesian method for parameter estimation and fragility model selection for mutually exclusive and collectively exhaustive (MECE) damage states making use of an adaptive Markov chain Monte Carlo simulation (MCMC) and based on likelihood estimation using point-wise intensity values.

7.2.2 Data and Technical Requirements

To develop the fragility models, databases of damage to the built environment collected after tsunami events are needed. Such databases must contain EVs and RVs. Most of the collected data and the developed models are event and country specific.

Among the EV, there is information about the hazard (i.e., the IMs), the affected asset (e.g., the building typology), and the local geomorphological conditions (i.e., Ria-type or Plain coast). Regarding the tsunami IM, a first attempt consists in retrieving them from the observation. This is generally feasible for the tsunami depth, even if some uncertainties exist due to judgement and spatial sampling (De Risi et al. 2017a). Simulation techniques are used when it is impossible to have a proper empirical estimation. For example, it is complicated to assess the tsunami flow velocity from video recordings of the events or sensors installed in buoys. It is also very complex to have such an estimation at urban or regional scales. Therefore, simulation values are often used as the IM in combination with other empirical values.

For what concerns the building typologies, a combination of governmental databases of the built environment and volunteered geographic information are typically used to characterise the affected assets. Such data are critical when buildings and constructions were entirely washed away (i.e., their posterior characterisation is impossible during the damage survey). Similarly, geomorphological features can quickly be investigated using observation of the topography.

Both building typology and topographic features can be used in two different ways. First, they may be used as a discriminant to define subsets of data to develop specific models. This first case is conventionally applied in OLS regression techniques. And second, they can become dummy variables; therefore, a single model is produced where all the data are used together as input. This is generally the case when GLMs are employed.

Regarding RVs, the damage states should have specific characteristics. First, they should be mutually exclusive and clearly distinguishable (e.g., no collapse, washed away). DS should be easily applied to populations of buildings. Finally, a division between structural and non-structural damage should be considered. As for some of the EVs, DSs can be used in two ways: i) creation of a subset of data, or ii) implementation in the model as dummy variables. As before, the first case is adopted for simple regression strategy. The second one is used for more sophisticated GLMs.

7.2.3 Treatment of Uncertainties

All the above-mentioned statistical regression methods provide a probabilistic interpretation of the observed data. The uncertainties associated with data are mainly epistemic and are associated with both the EVs and the RVs.

Regarding the IMs, uncertainties are associated with the data acquisition methods and/or with the computational models used to simulate missing data. For example, the tsunami inundation depth may be subjected to uncertain assessment associated with the survey method (e.g., wet marks on the walls or on the nearby still-standing infrastructures). Similarly, the tsunami velocity assessment can be affected by the data acquisition method (e.g., video interpretation) or by the simulation approach and grid resolution. Such uncertainties can be assessed and quantified either using

multiple damage databases or using multiple tsunami inundation numerical models. De Risi et al. (2017a) provides an example of quantification and propagation of uncertainties on IMs. Regarding the DSs, an innovative method to propagate their uncertainties has been proposed by Jalayer et al. (2022). Both approaches above are based on Bayesian statistics; in fact, Bayesian methods constitute the ideal set of tools for such a task.

Conventional approaches to convey uncertainties consist of computing the variability of the model parameters (e.g., variance of the median and the logarithmic standard deviation). Such quantification of the uncertainty will allow to provide fragility curves and pre-defined confidence intervals (Table 7.2).

7.3 Analytical Physical Vulnerability

7.3.1 Short Description

All analytical physical vulnerability models are indirect and based on an evaluation of physical asset fragility. For the analytical assessment of fragility, a damage scale needs to be defined and mechanics-based damage states (DS) should be clearly described. Fragility functions can then be transformed into a vulnerability function using consequence models, which are derived based on reconstruction costs data from past tsunami events (if any). As an alternative, numerical simulations of reconstruction costs can be adopted. Up to now, there is a lack of available consequence functions for tsunami events, hence the following text focuses on tsunami fragility analyses.

Like the methods for deriving fragility curves in case of earthquake actions on structures, static or dynamic, linear or nonlinear structural analyses are performed for the assessment of structural response under tsunami loads and to define structural capacity and specific damage states (e.g., slight, moderate, extensive and complete). Once the structural responses and expected damage states under a range of tsunami intensity levels are analytically simulated, statistical processing similar to that used for empirical fragility function development is applied to this dataset to generate analytical fragility functions. The analytical simulation typically requires the development of structural models using finite element modelling (FEM). Examples of FEM packages that have been used for tsunami vulnerability simulations include OpenSees (McKenna et al. 2010) and SeismoStruct (SeismoStruct, 2022).

Tsunami forces are based on flow conditions and are mainly classified as hydrostatic forces under the quiescent flood states, buoyant forces resulting from vertical hydrostatic forces due to the volume of water displaced by a fully or partially submerged structure, hydrodynamic forces induced by steady flows, highly transient impulsive forces at the impact of the leading edge of the arriving water mass, debris impact forces caused by waterborne debris, and debris damming force due to the accumulation of debris across the structure (FEMAP-646, 2012).

Table 7.2 Summary table for empirical physical vulnerability

Short description of method	
Short outline of how the method works	The empirical vulnerability consists of a set of statistical models correlating some EVs to some RVs based on observed tsunami events. Explanatory Variables are both IMs and characteristics of the built environment. The typical RV is the DS, representing a damage condition experienced by the asset of interest after the tsunami. DS may vary from zero damage up to washed away (total damage)
How is/are the output(s) of the method(s) represented?	Empirical vulnerability models are usually presented as fragility curves, which are statistical relationships between the IMs and the probability of attaining a specific damage state conditioned on the IM
Do(es) the method(s) use parallelisation, machine learning, surrogate models, advanced simulation schemes, other computational reduction strategies (e.g., cluster analysis, etc.)?	ML algorithms have been used to develop such models. As such models do not need computational power as they are statistical tools, no cluster analysis or parallelisation is required. The machine learning approach may require more computational time as some model training is needed
What are the pros and cons and peculiarities of this specific method(s)? Are there known shortcomings / benefits of the method(s)? In what cases is this method(s) a good/poor choice?	Empirical tsunami vulnerability functions are, by definition, specific to the event and the location affected by the tsunami. Also, both IMs and building damage are typically recorded in visual inspections after the event. Hence, it is often difficult to accurately determine the actual IM. In addition, damage observations for buildings that are subject to both earthquake and tsunami may be due to both perils, increasing the uncertainty
Data and technical requirements for method	
What input data does the method(s) use?	Databases of damage to the built environment collected after tsunami events are needed. Such databases must contain EVs and RVs. Most of the collected data and the developed models are event-specific and country-specific
What are the technical requirements?	Typical statistical methods used for the development of empirical vulnerability models are the OLS, and the GLM
Treatment of uncertainties for the method	
Is the method(s) itself deterministic or uncertainty based?	The statistical regression methods provide a probabilistic interpretation of the data
Which are potential sources of uncertainties? Which parameters are used to characterize them?	The uncertainties associated with data are mainly epistemic and are associated with both the EVs and the RVs

(continued)

Table 7.2 (continued)

How are uncertainties quantified for the identified parameters? Are there significant correlations between different uncertain parameters?	Uncertainties in IMs are associated with the data acquisition methods and/or with the computational models used to simulate missing data. Novel approaches are based on Bayesian statistics; in fact, Bayesian methods constitute the ideal set of tools for such a task
Is the method(s) able to digest and propagate uncertainty in input (previous ingredient) and propagate it to the output (next ingredients)? Does the assessment of this ingredient require uncertainty propagation? If yes, how are uncertainties propagated?	Conventional approaches to convey uncertainties consists of computing the variability of the model parameters. Such quantification of the uncertainty will allow to provide fragility curves and pre-defined confidence intervals

Several experimental investigations have been conducted to evaluate the wave-structure interaction. Some of these focused on the generation of tsunami-like waves in hydraulic flumes (among others, Hamzah et al. 2001; Rossetto et al. 2011; Palermo et al. 2012; Chinnarasri et al. 2013; Park et al. 2013; Qi et al. 2014; Shafiei et al. 2016; Foster et al. 2017; Alam et al. 2020). The experimental measurements can provide valuable information on hydrodynamic flow conditions as well as lateral and vertical forces and pressures exerted on the structure.

Commonly used IMs for the development of tsunami analytical fragility curves are inundation depth, flow velocity, and specific momentum flux. Attary et al. (2017) proposed a methodology for the development of physics-based tsunami fragility curves using vector valued IMs, such as tsunami flow depth and flow velocity and several combinations thereof, relying on Monte Carlo Simulation to consider the material uncertainties and for epistemic uncertainties in the tsunami force calculation.

Different types of structural analysis can be selected for performing tsunami analytical fragility assessment of a facility, but these can be grouped into two main classes: (a) static analysis (pushover); and (b) dynamic time-history analysis. Nonlinear static analysis methods neglect the dynamic response of structures and apply tsunami loads in a static manner. Hydrodynamic forces are typically applied to each inundated story of the building along the seaward columns, assuming a constant tsunami inundation depth and increasing flow velocity, as illustrated in Fig. 7.4a. This approach is referred to as constant-depth pushover (CDPO). CDPO is similar to a seismic pushover analysis and can be implemented easily in commercial structural analysis software. Attary et al. (2017) and Alam et al. (2018) performed CDPO analyses in a fragility assessment of reinforced concrete structures, accounting for the local members' failure, e.g. columns.

Novel analysis methods developed by Petrone et al. (2017) are the tsunami time-history dynamic analysis (TDY) and the variable depth pushover (VDPO). TDY analyses are based on the same principle as a seismic time-history dynamic analysis, except for the input data. The latter typically consists of wave traces (i.e., tsunami inundation depth and flow velocity time-histories). These records can be generated

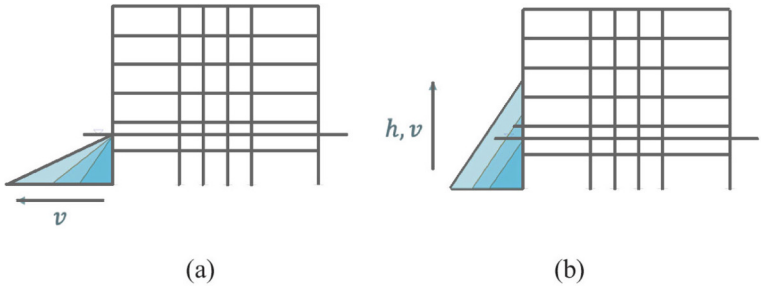

Fig. 7.4 Schematic illustration of recently proposed tsunami pushover analysis: **a** constant depth pushover; and **b** variable depth pushover

with numerical simulations (Goda et al. 2017). The VDPO analysis is a static analysis, where the tsunami force applied to the structure is increased incrementally by increasing the tsunami inundation depth monotonically, as illustrated in Fig. 7.4b. At each depth value, the corresponding flow velocity is calculated assuming a constant Froude number (*Fr*). Petrone et al. (2017) found that the VDPO analysis outperforms the CDPO analysis in terms of engineering demand parameter estimation, (i.e., inter-story drifts and column shear forces).

However, the VDPO as originally conceived in Petrone et al. (2017) is a load-control analysis, and therefore, it is not capable of capturing the degrading behaviour of the structure. This limitation is overcome by the so-called VDPO2 approach, developed by Baiguera et al. (2022). VDPO2 consists in a two-phase nonlinear static: in the first phase a load-control pushover analysis is carried out assuming that the inundation depth and flow velocity increase incrementally; in the second phase, the analysis switches to response-control pushover analysis, where the displacement is gradually increased, and the corresponding tsunami force is calculated. The switch from the first phase to the second one occurs either when a predefined load level is reached or when the analysis encounters a numerical convergence issue, whichever occurs first. The VDPO2 is referenced in ASCE7-22 (2022) as a recommended nonlinear static method for the tsunami design of buildings exposed to tsunami risk.

The VDPO method has been further enhanced for the analysis of reinforced concrete frames with breakaway infill walls. Del Zoppo et al. (2021) developed a bespoke method, referred to as VDPO-BI, in which the tsunami-induced lateral and vertical loads are monotonically applied to structural and non-structural components as a function of the tsunami inundation depth, up to the structural collapse (Del Zoppo et al. 2019). A mechanics-based method to develop fragility curves at community level has been proposed in Del Zoppo et al. (2022) with the application of the VDPO-BI analysis. In the case of masonry structures, Belliazzi et al. (2021) proposed methods to perform the damage assessment and develop fragility curves.

Most of the currently available analytical tsunami fragility curves have been developed at single-building level (e.g., Petrone et al. 2017; Alam et al. 2018). Although earthquakes are the primary trigger of tsunamis, few studies have investigated the impact of earthquake damage in deriving tsunami fragility curves (Park et al. 2012;

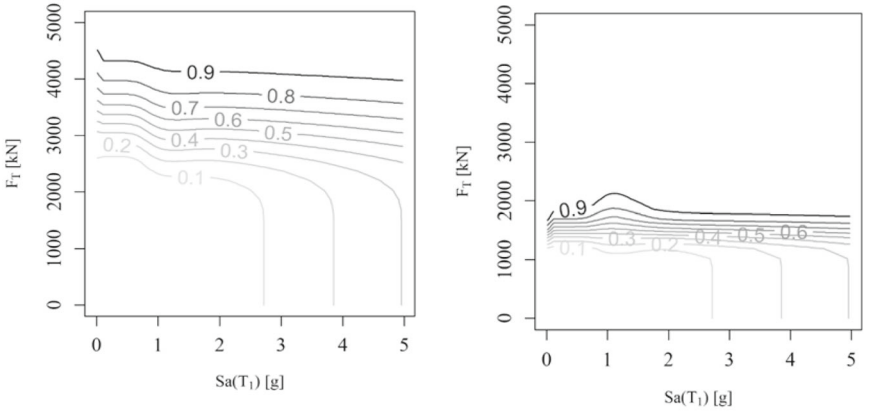

Fig. 7.5 Collapse fragility surface for a reinforced concrete building under sequential earthquake and tsunami: **a** global performance; and **b** local performance (Petrone et al. 2020)

Latcharote, 2015). Petrone et al. (2020) developed the combined earthquake-tsunami fragility curve for the first time for a reinforced concrete building, accounting for the global performance as well as the influence of local failure of structural components (see Fig. 7.5). A full nonlinear response history analysis of the building was used to simulate the earthquake and tsunami loading in sequence, since Rossetto et al. (2019) found that use of a static analysis for representing the earthquake damage, followed by a tsunami dynamic analysis, results in over-conservativism.

7.3.2 Data and Technical Requirements

To develop analytical fragility curves, input data related to the assets geometric and mechanical properties, and structural details must be known. For existing assets, structural details can also be derived from a simulated design process. Fragility curves are analytically derived for the assets under investigation performing a damage assessment through refined structural analyses in a probabilistic framework. Indeed, uncertainties related to load demand and structural capacity should be properly modelled.

The damage assessment should account for all the tsunami-induced loads and effects on structure and infrastructure. According to the ASCE7-22, (2022), a tsunami flow induces lateral and vertical (uplift) hydrostatic and hydrodynamic pressures on structure and infrastructure. Such flow can be considered as quasi-steady according to Qi et al. (2014), and the induced lateral pressure can be computed following the empirical equations proposed by Foster et al. (2017). Tsunami flows are unsteady; however, they can be considered quasi-steady when due to their extremely long

wavelengths, the temporal variation of the flow is small, especially with respect to the lifetime of a building. There are no empirical models for induced uplift loads on structures, hence the equations provided by the ASCE 7–22 can be adopted to compute such load values. Besides the hydrostatic and hydrodynamic pressure, tsunami also induces impulsive loads, debris impact loads and scour. ASCE 7–22 provides models to compute such impulsive and impact loads on structure and infrastructure. About the scour, the American Standard provides information about the maximum scour depth induced by a tsunami, but research is ongoing to assess the evolution of the scour depth during the inundation (McGovern et al. 2019).

The most common IM adopted in both empirical and analytical tsunami vulnerability models is the inundation depth. Indeed, the inundation depth is easily measurable in the aftermath of a tsunami and can be simulated numerically with relatively small errors. However, recent analytical studies have observed that other parameters, such as the momentum flux, can be also adopted as IM given the good correlation with damages and losses (Park et al. 2017). The efficiency of vector-valued IMs consisting of scalar IMs such as inundation depth, flow velocity, specific momentum flux, kinematic moment of specific momentum flux, and their interactions were investigated by Alam et al. (2018) against the conventional scalar IMs. It was observed that the estimation efficiency of vector-valued IMs is higher than that of scalar IMs and the prediction of structural damage using vector-valued IMs can be further improved by considering the interaction among the IMs.

Different modelling approaches have been adopted for simulating physical assets and their response to tsunami loads. The asset modelling is of critical importance to the reliability of the resulting fragility function. In particular, the FEM model should be able to represent both global and local damage mechanisms under the horizontal and vertical loading imposed by tsunami inundations. Inevitably, this results in more sophisticated FEM modelling of buildings being required, and models based on single degree of freedom systems (e.g., Park et al. 2017) should be avoided. The complexity of the structural modelling needed is one of the reasons that analytical fragility functions have predominantly been derived for single buildings, or representative index buildings. Moreover, the modelling or assessment of structural element shear response is critical, as tsunami inundation loads impart high shear forces to structural elements (in particular, ground floor vertical elements in structures). It is noted that the local shear failure of vertical elements can lead to premature structural collapse, as shown in Petrone et al. (2017) and Petrone et al. (2020).

7.3.3 Treatment of Uncertainties

Uncertainties from demand parameters in tsunami loading (e.g., drag coefficient, among others) as well as in structural capacity modelling (e.g., material strength, structural details) should be accounted for and modelled during the fragility and

vulnerability analysis. Capacity of structures, IM and tsunami-induced loads represent potential sources of uncertainties. Geometric and mechanical properties of materials are epistemic variables that should be considered with their probability distributions and statistics. Indeed, it is hard to achieve a full knowledge about the exact geometry, structural detailing and material properties of an existing building, and the level of knowledge is much lower when dealing with large scale fragility assessment. Epistemic uncertainties related to the modelling and structural analysis method should also be considered when assessing the structural capacity and damage. Only a few empirically validated models are available to simulate the tsunami loads and effects on structures (e.g., effect of openings, damming debris accumulation, debris impact, and scour), and available models can be affected by errors. Uncertainty in the tsunami load parameters (e.g., flow depth and velocity) need to be considered as well. Alam et al. (2018) observed that uncertainty in the IM is more sensitive to uncertainties in the tsunami demand parameters than those in the structural model idealisation. This implies that an improved understanding of the characteristic tsunami flow information, with a specific focus on flow velocities, will significantly reduce the uncertainty in the fragility curves.

Uncertainties related to the fragility of buildings can be quantified for the specific site and assets under investigation based on available historical data collected from literature about typical material types, material properties and structural design in the specific site, open data repositories on assets, such as OpenStreetMap, or in-situ surveys (Baiguera et al. 2021; Cels et al. 2023). One of the major challenges in incorporating uncertainty in fragility function development is the balance between computational demand and accuracy. Among the available methods, Monte Carlo-based simulation is considered as the most comprehensive one. However, to improve computational costs, importance sampling methods, such as Latin hypercube sampling, response surface, or artificial neural networks can also be used. Alam et al. (2018) used the First-order Sampling Method (FOSM) to propagate the uncertainty from demand parameters (e.g., tsunami loading) and structural capacity modelling to structural response estimation (Table 7.3).

7.4 Indicator-Based Vulnerability

7.4.1 Short Description of Method

Physical vulnerability has been defined as the degree of loss of a given element (e.g., buildings) that is affected by the impact of a natural process (UNDRO, 1984) and can vary from 0 (no loss) to 1 (total loss), when only direct losses are assessed. This definition suggests that vulnerability equals the consequences of this impact and is not related to a pre-existing condition, weakening in this way the predictive power of its assessment. By accepting the newer more general definition of vulnerability

Table 7.3 Summary table for analytical physical vulnerability

Short description of method	
Short outline of how the method works	The analytical vulnerability consists of a set of statistical models correlating some EVs to some RVs based on simulated tsunami scenarios. Explanatory Variables are both IMs and characteristics of the built environment. The typical RV is the DS, representing a damage condition experienced by the asset of interest after the tsunami. DS may vary from zero damage up to washed away (total damage)
How is/are the output(s) of the method(s) represented?	Fragility functions, consequence functions, and vulnerability functions
Do(es) the method(s) use parallelisation, machine learning, surrogate models, advanced simulation schemes, other computational reduction strategies (e.g. cluster analysis, etc.)?	The analytical simulation typically requires the development of structural models using FEM. Examples of commercial FEM packages that have been used for tsunami vulnerability simulations include OpenSees and SeismoStruct
What are the pros and cons and peculiarities of this specific method(s)? Are there known shortcomings / benefits of the method(s)? In what cases is this method(s) a good/poor choice?	One of the major challenges in incorporating uncertainty in fragility function development is the balance of computational demand and accuracy. Among available methods, Monte Carlo-based simulation is the most comprehensive method. However, to improve computational costs, importance sampling methods such as Latin hypercube sampling, response surface, or artificial neural networks can also be used
Data and technical requirements for method	
What input data does the method(s) use?	Input data related to the assets geometric and mechanical properties, and structural details should be known. For existing assets, structural details can also be derived from a simulated design process. Fragility functions are analytically derived for the assets under investigation performing a damage assessment through refined structural analyses in a probabilistic framework. The damage assessment should account for all the tsunami-induced loads and effects on structure and infrastructure
What are the technical requirements?	Different types of analysis can be selected for performing tsunami analytical fragility assessment of a facility. The structural analysis may be linear or nonlinear, depending on the nature of the materials constituting the building (e.g. confined masonry, steel frame, reinforced concrete), and either static or dynamic

(continued)

Table 7.3 (continued)

Treatment of uncertainties for the method	
Is the method(s) itself deterministic or uncertainty based?	The statistical regression methods provide a probabilistic interpretation of the data
Which are potential sources of uncertainties? Which parameters are used to characterize them?	The uncertainties associated with data are mainly epistemic and are associated with both the Explanatory Variables and the Response Variables. Geometric and mechanical properties of materials are aleatory variables that should be taken with their probability distributions and statistics. Only a few empirically validated models are available to simulate the tsunami loads and effects on structures (effect of openings, damming debris accumulation, debris impact, scour), and also available models can be affected by errors. Uncertainty in the tsunami load parameters (flow depth and velocity) need to be considered as well
How are uncertainties quantified for the identified parameters? Are there significant correlations between different uncertain parameters?	Uncertainties can be quantified for the specific site and assets under investigation based on available historical data collected from literature, open-source repositories, Open Street Maps, or in-situ surveys

(UNDRR, 2017) "*the conditions determined by physical, social, economic and environmental factors or processes, which increase the susceptibility of an individual, a community, assets or systems to the impact of hazards*", we accept that vulnerability is a pre-existing condition related to the characteristics of the elements at risk. Indicators can operationalise these characteristics (Birkmann, 2006) and form the basis for the development of an index that can express vulnerability qualitatively.

Indicators are widely used for the assessment of social vulnerability and may include information on age, health status, income, educational level, etc. In the case of physical vulnerability of buildings to tsunami the physical vulnerability indicators are operational representations of building exposure characteristics (e.g. building material, openings, etc.) or characteristics of their surroundings (e.g., surrounding vegetation or wall) that influence the overall vulnerability of the building to tsunamis. The theoretical background is described in detail in *Chapter 2*. One of the most-established indicator-based methods for tsunami focusing on physical vulnerability is the Papathoma Tsunami Vulnerability Assessment (PTVA). This method was first proposed in 2003 and has been applied to case-studies in Greece (Papathoma and Dominey-Howes, 2003). It was further developed following the 2004 Indian Ocean Tsunami (Dominey-Howes and Papathoma, 2007). The weighting method has been improved in further versions of the PTVA (DallOsso et al. 2009a; DallOsso et al. 2016) and has become a popular method as it has been validated and used in several countries. It has also been adapted for different hazards, including dynamic flooding

(Papathoma et al. 2019) and wildfire (Papathoma et al. 2022). A stepwise description of the method is illustrated in Fig. 7.6.

PTVA has been applied in Italy (DallOsso et al. 2010), Iran (Madani et al.2017), Chile (Izquierdo et al. 2018), Portugal (Santos et al. 2014), Australia (Dall'Osso et al. 2009b, 2016), in Indonesia for critical infrastructure (Husrin et al. 2013) and school buildings (Gentile et al. 2019), in Japan (Voulgaris and Murayama, 2014), in Malaysia (Ismail et al. 2012) and Sri Lanka (Sathiparan, 2020; Hasalanka et al. 2021). An overview of the indicator-based applications is presented in Table 7.4.

Indicator-based methods should account for the fact that vulnerability changes through space and time, therefore, they should be updated regularly to account for future changes. The GIS database containing vulnerability indicators for the buildings of the study area can be easily updated to describe the current situation and condition

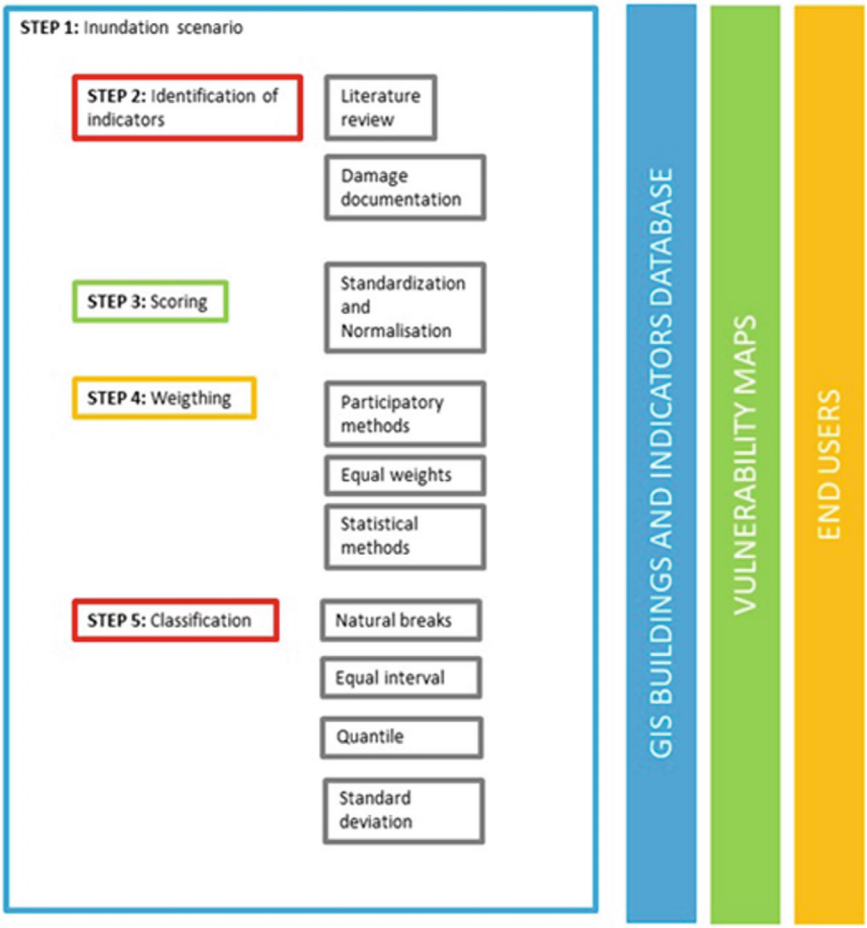

Fig. 7.6 Indicator-based vulnerability assessment workflow based on the PTVA method

Table 7.4 An overview of some of the studies that have applied the PTVA approach

Study	Country	Special focus	Application	Comments	Source of inundation map
Omira et al. (2010)	Morocco (Casablanca)	Buildings	Potentially for building modification and evacuation planning	Inspired from PTVA (only three indicators used)	Numerical modelling of the 1755 tsunami
Santoset al. (2014)	Portugal (Setubal city in Lisbon metropolitan area)	Buildings including services (police station, fire brigade, administrative buildings)	Validation of historical records from the 1755 tsunami. Potentially it could be used for urban planning	Use of PTVA but no comparison with another model (Ismail et al. 2012)	Numerical model of the 1755 tsunami
Voulgaris and Murayama (2014)	Japan	Buildings	None	PTVA Combined with population data	Imamura-Iida tsunami magnitude scale was used to calculate the maximum run-up for an 8.2 M earthquake
Alberico et al. (2015)	Italy (Naples)	Urban area (Census district)	Possibilities to reduce vulnerability (interventions), locations for vertical evacuation	PTVA applied to a different scale. The unit is not the building but the census district	Tsunami hydrodynamic modelling of a historic tsunami caused by a submarine debris avalanche in Ischia
Madani et al. (2017)	Iran (Chabahar Bay)	Buildings (residential area)	None	Use of PTVA	Numerical modelling of a Makran subduction worst-case scenario

(continued)

Table 7.4 (continued)

Study	Country	Special focus	Application	Comments	Source of inundation map
Izquierdo et al. (2018)	Chile	Buildings	Validation through a real event (2015), focus on historical buildings	PTVA material indicator was modified according to construction types in Chile	Reconstructed tsunami inundation map and flow depths from the data collected in the field after the 2015 tsunami
Batzakis et al. (2020)	Greece (Santorini)	Buildings (touristic area)	Potentially, Tsunami building codes and early warning systems	Use of PTVA	Static inundation method (run up based on previous studies)
Hasalanka et al. (2021)	Sri Lanka	Hospitals	Disaster risk management	Changes to PTVA are recommended to include hospital–relevant indicators	Potential tsunami scenarios based on available risk maps

of buildings. Moreover, the vulnerability index can be used during the reconstruction process to assess the quality of BBB (Build Back Better). Additionally, indicator-based methods could be expanded to include indicators related to the functionality of a building. For example, Baiguera et al. (2021) proposed a simple but quantitative approach for the assessment of the resilience of healthcare systems to tsunami. This is based on indicators that relate not only to hospital building fragility, but also to the maintenance of hospital functionality. The impact of tsunami on hospital critical units (e.g., Intensive Care Unit) in individual hospitals, as well as the impact on service provision across a network of hospitals, is measured through the Tsunami Relative Risk Index (TRRI). The ability of a hospital critical unit to function in the aftermath of a tsunami depends on three components: 1) the fragility of the structure where the hospital critical unit is located (i.e., the "building component"); 2) the integrity of non-structural elements relevant to the critical units, (e.g., the medical equipment that is required to ensure unit functionality); and 3) the functioning of the critical lifeline systems supporting unit functionality (e.g., electric power, water supply, telecommunications, etc.). It is noted that the main difference between the "building component" and the PTVA, is that the former one is based on a simplified assessment of the building failure and damage mechanisms, evaluated using physics and engineering-based formulations.

7.4.2 Data and Technical Requirements for Method

The main data required for the implementation of the indicator-based methods include geospatial data (e.g., building footprints), information on building characteristics and their surroundings and detailed information on past tsunami events or inundation modelling results for specific scenarios. This reflects the deterministic nature of the method. An expert panel should also develop a set of case study-related indicators. This expert panel should include local experts including researchers, engineers and environmental experts to develop an indicator dataset which is relevant to the local context, but also social scientists or economists if the vulnerability assessment is to be extended to include additional vulnerability dimensions (e.g., social). The main requirement involves detailed data on the buildings collected during extensive fieldwork. These data may include the number of floors, the building material, the use of the ground-floor, the building row facing the coast, the surrounding wall or vegetation and the presence of barriers between the building and the water. Alternative methods for data collection may include *Google Street View*, other remote sensing methods, existing inventories, *Youtube* videos or questionnaires completed by the house owners. Potential developments of the method could include using the *Boruta* algorithm (Kursa and Rudnicki 2010) for the weighting of indicators, using alternative methods for data collection and the inclusion of socioeconomic data to assess further vulnerability dimensions.

Indicator-based methods have many potential applications for disaster management and disaster risk reduction. Some of them are described in one of the first applications of the PTVA (Papathoma and Dominey-Howes, 2003). Applications may include the use of the vulnerability map as basis for decision-making (e.g., targeted building strengthening or relocation). Moreover, the combination of indicator-based methods with demographic data may support targeted evacuation and rescue planning, as well as public awareness and education programs. In any case, uncertainties related to the potential inundation zone, the quality of input data and the expert judgement may contribute to an overestimation or underestimation of physical vulnerability and must be treated before being used for decision-making. Nevertheless, as far as PTVA is concerned, uncertainties have not been addressed until now. In-depth information on the method can be found as supplementary material together with the latest publication (Dall'Osso et al. 2016). In more detail, the supplementary material contains an ARCGIS toolbox (PTVA4_Toolbox), a shapefile for the exposed buildings in the case study area and an Excel file with the questionnaire sent to the experts (Table 7.5).

Table 7.5 Summary table for indicator-based vulnerability

Short description of method	
Short outline of how the method works	Indicator-based methods make use of vulnerability indicators to assess the physical vulnerability of buildings to tsunamis. The vulnerability indicators are operational representations of building characteristics or characteristics of their surroundings that influence the overall vulnerability of the building to tsunamis
How is/are the output(s) of the method(s) represented?	The degree of loss of a given element (e.g., buildings) that is affected by the impact of the tsunami, which can vary from 0 (no loss) to 1 (total loss)
What are the pros and cons and peculiarities of this specific method(s)? Are there known shortcomings / benefits of the method(s)? In what cases is this method(s) a good/poor choice?	Indicator-based methods have many potential applications for disaster management and disaster risk reduction. For this reason, indicator-based methods have become a popular method: they have been validated through past tsunami events and expert elicitation. The indicator-based methods can be adapted to future changes. The GIS database containing vulnerability indicators for the buildings of the study area can be easily updated to describe the current situation and condition of buildings. The vulnerability index can also be used following a catastrophic and after the reconstruction process has been completed to demonstrate the BBB (Build Back Better)
Data and technical requirements for method	
What input data does the method(s) use?	Indicator-based methods require Geographic Information Systems (GIS), detailed information on past tsunami events or modelling possibilities and an expert panel by developing a set of case study-related indicators. Detailed data on the buildings collected during extensive fieldwork are needed. Alternative methods for data collection may include Google Streetview, other remote sensing methods, existing inventories, Youtube videos or questionnaires completed by the house owners
Treatment of uncertainties for the method	
Is the method(s) itself deterministic or uncertainty based?	The method has been mostly used for deterministic case studies

7.5 Social Vulnerability

7.5.1 Short Description of Method

Social vulnerability refers to the susceptibility of individuals and social groups to the adverse impacts of natural hazards, including disproportionate death, injury, financial and non-financial loss (e.g., loss to household assets, health) and disruptions to livelihood (Cutter et al. 2012; Birkmann et al. 2013). Social vulnerability has so far not been included in mainstream probabilistic tsunami risk assessment. However, the impact of tsunami on mortality, fertility, health, schooling and business continuity has been documented in the empirical economics literature, based on the analysis of large-scale household survey data before and after the hazard occurred (Cas et al. 2014; Frankenberg et al. 2011; Nobles et al. 2015; Himaz, 2022; Syukriyah and Himaz 2024). This literature is a subset of the wider, but still relatively young field of disaster impact evaluation in applied microeconomics.

A seminal effort to capture social vulnerability in tsunami risk assessment can be seen in Salmanidou et al. (2021). The empirical framework correlates EVs to RVs based on a observed tsunami event, the 2006 Java earthquake and tsunami with data coming from a survey of about 6,000 households. EVs are IMs and pre-tsunami impact characteristics at the household level. Although IMs such as the tsunami inundation depth can be used, they should be matched against each household in the sample. In the absence of such data, this study proposed to use a proxy measure of intensity that is constructed using field-level observations carried out by experts knowledgeable about the local area. These are calibrated for accuracy using before-after satellite imagery or remote sensing data. Considering vulnerabilities that may build up before the event, EVs are characteristics for the household just before the tsunami such as wealth, urban or rural location. The RV used in this study is loss ratio of the value of assets experienced by households, calculated as a percentage change to asset value using data just before and just after the tsunami. Assets include land, buildings, vehicles, furniture, livestock, jewellery, and hard-wood trees. The value of these RVs can vary from 0 to 100%. The OLS method is used to understand the impact of tsunami on damage to household assets. Multinomial logit regression modelling is used to estimate the distributions of damage by tsunami intensity.

Theoretically, RVs can capture negative impacts to various microeconomic indicators. At the level of the individual this can be, for example, the damage to earnings, mental and physical health, or schooling. At the household-level it can be the damage to assets or household standing in terms of poverty or wellbeing. At the community level, the indicator could be crime rates. Although the range is wide, there are two major econometric challenges to generating meaningful vulnerability functions

(Anttila-Hughes and Sharma, 2015; Porter and White, 2016). The first is the so-called 'internal validity', which refers to the establishment of a causal (or, at least, externally replicable) relationship between IMs and the microeconomic damage indicator. If the damages attributed to a tsunami are the result of the tsunami per se as well as other factors such as wealth and attitudes to risk, then the estimates may be biased. The second is the so-called 'external validity', or the extent to which assessed impacts can be generalised out of the sample, either to other contexts or locations, or to other time periods. Further discussion regarding internal and external validity can be found in Angrist and Pischke (2009).

7.5.2 Data and Techniques

Tsunami social vulnerability modelling requires large scale panel household survey data with detailed before-after information and objective IMs that can be linked to the unit of analysis (i.e., individual, household or community). A good example of such data is the Study of the Tsunami Aftermath and Recovery (STAR: http://stardata.org), a longitudinal survey carried out in Aceh and North Sumatra, Indonesia. The survey collected data on individuals, households, communities and facilities to provide evidence on the immediate and longer-term consequences of the 2004 Indian Ocean Tsunami. The first round of data was collected 5–14 months after the tsunami from over 6000 households from 487 communities. It also included retrospective information collected from households on pre-tsunami characteristics enabling before-after comparisons and accounting for vulnerabilities that built up before the event. The first round of data was followed by further annual rounds of data collected for four years from the same households with a 10-year follow-up survey. The data contains information on employment, income, spending, schooling, health, household and business assets, attitudes to risk, housing, migration and various other aspects. This enables the use of the data to create RVs capturing various dimensions of vulnerability. Data from this specific context, however, may not be applicable to other contexts across time and space. This is the issue of external validity discussed earlier. Tsunami-specific longitudinal surveys such as STAR are sparse, and an alternative source may be repeated cross section data collected from the same area before and after a tsunami. The latter data may be used to estimate community-level impacts. For example, Sri Lanka's Household Income and Expenditure Surveys conducted in 1990, 1995, 2002 and 2005 by the Department of Census and Statistics may be used to assess changes to consumption, income or spending at the level of an administrative unit such as a community or village, providing the geographical units can be linked over time. Apart from this, other data and techniques found in the wider

economic and impact evaluation literature may be considered when estimating social vulnerability. These include constructing pseudo-panels with repeated cross sections (Verbeek, 2008), using administrative data (Wang et al. 2016; Karlan et al. 2016) and satellite and remotely sensed data (Heger and Neumayer, 2019). Even so, the relative rareness of tsunamis and the subsequent unavailability of historical data enabling the constructing of microeconomic indicators and IMs, as well as the small sample size in cases where data is available constrain the development of internal and externally valid estimates, and therefore meaningful tsunami social vulnerability functions.

7.5.3 Treatment of Uncertainties

In household survey data, systematic errors can arise from non-random biases in recollection data (such as respondents' recollection of pre-tsunami assets 12 months after the tsunami being systematically different to that reported 24 months after the event as noted in Himaz, (2022)), sample selection biases (arising from the people affected by the tsunamis being systematically different to those who were not affected) and non-random sample attrition in longitudinal surveys. Such systematic errors can bias the parameters estimated such that a causal interpretation cannot be given to an estimated parameter.

Various data design methods and statistical techniques can be used to address some of the issues especially in the context of impact evaluation (Angrist and Pischke, 2009). Usually, robustness checks using alternative specifications, data sources and statistical methods are used to validate results. Fundamentally, however, good quality, credible data is essential to measure social vulnerability accurately. About IMs, the discussion in Sect. 7.2.3 in the treatment of uncertainties in physical vulnerability models is relevant to social vulnerability.

Measures to convey uncertainty include measures that compute the variability of model parameters (standard errors, statistical significance, variance of the median, etc.), allowing to provide fragility curves with pre-defined confidence intervals (Table 7.6).

Table 7.6 Summary table for social vulnerability

Short description of method	
Short outline of how the method works	Social vulnerability is about the evaluation of the impact of tsunami on social outcomes, such as mortality, fertility, health, schooling and business continuity. This area of research is strongly linked to empirical economics. A social vulnerability framework aims to correlate EVs RVs based on an observed tsunami event. Examples of EVs are IMs (e.g. tsunami inundation depth) and pre-tsunami impact characteristics at the household level. RVs can vary from microeconomic indicators (e.g., damage to household assets) to community-level indicators (e.g., crime rates)
How is/are the output(s) of the method(s) represented?	The OLS method may be used to understand the impact of tsunami on damage to household assets. Multinomial logit regression modelling may be used to estimate the distributions of damage by tsunami intensity
What are the pros and cons and peculiarities of this specific method(s)? Are there known shortcomings / benefits of the method(s)? In what cases is this method(s) a good/poor choice?	There are two major econometric challenges to generating meaningful social vulnerability functions: (a) 'internal validity', which refers to the establishment of a causal (or, at least, externally replicable) relationship between IMs and the microeconomic damage indicator; (b) 'external validity', or the extent to which assessed impacts can be generalised out of the sample, either to other contexts or locations, or to other time periods
Data and technical requirements for method	
What input data does the method(s) use?	Tsunami social vulnerability modelling requires large scale panel household survey data with detailed before-after information and objective IMs that can be linked to the unit of analysis (i.e., individual, household or community). Such data are sparse and other techniques found in the wider economic and impact evaluation literature such as constructing pseudo-panels with repeated cross sections, using administrative data, satellite and remotely sensed data may be considered
Treatment of uncertainties for the method	
Is the method(s) itself deterministic or uncertainty based?	The statistical regression methods provide a framework for probabilistic interpretation of the data

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